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Essays on the Industrial Organization and Regulation of Recreational Cannabis Markets

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Essays on the Industrial Organization and Regulation of Recreational Cannabis Markets

by

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Dedicated to my family.

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Essays on the Industrial Organization and Regulation of Recreational Cannabis Markets

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This dissertation addresses open questions in economics surrounding the industrial organization and regulation of recreational cannabis markets. The first chapter empirically studies how the impact of location restrictions on strategic cannabis retailers affects market outcomes and resident welfare. The second chapter provides a different method to measure the externality that cannabis retailers impose on heterogeneous residents and how it varies with different land-use policies. The third chapter investigates the presence of consumer demand response and inertia in vertical relationships among buyers and sellers in a new market.

The first chapter studies the welfare impact of land-use regulations, such as location restrictions for businesses, which generally involves a trade-off between market growth and the harm on affected parties and is ultimately an empirical question. I study how location restrictions near sensitive-use areas affect recreational cannabis retailers' decisions in Washington State and their effects on residents, consumers, and taxation. Using property sales data, I first show reduced-form evidence that cannabis retailers act as a disamenity when close to homes and to their assigned schools. Then, I develop a structural model of consumer demand and firm entry and location and estimate it on a comprehensive dataset of retail sales and inventory transfers. The model incorporates the various market regulations as

constraints on the firms' strategic decisions. I use the estimated model to conduct counterfactual land-use policies. Relaxing buffers around sensitive-use areas, like schools, from 1000 ft down to 100 ft benefits consumers and harms residents but, on net, results in welfare and tax revenue improvements.

The second chapter is a more in-depth study of the other side of the coin, resident disamenities of cannabis retailers, where I develop a discrete-choice, static model of housing demand and supply, and estimate it with property sales and mortgage applicants data from King County, Washington. By allowing for heterogeneous households, I can incorporate the role of cannabis retailers as a potential (dis)amenity to households. I then compute the welfare impact of various alternative location configurations for retailers that arise from the counterfactual land use policies studied in Larsen (2020*b*). I find that resident surplus decreases on average but that the valuation for cannabis retailers is heterogeneous, with residents with children being the main demographic negatively affected.

Lastly, the third chapter studies the supply chain of the market to understand the factors that make-or-break vertical relationships and how a market matures. The third paper uses a rich dataset of inventory transfers for the Washington State recreational cannabis industry to assemble a novel dataset of vertical relationships between producers and retailers starting from the market's inception. In the early stages of the market, I find substantial structural state dependence within vertical relationships, suggesting firms are reluctant to sever their existing business links due to poorly performing products and serves as a cautionary tale against making assumptions about firms when not in equilibrium. As the market reaches an equilibrium, product performance becomes the leading factor for producer-retailer matching. A theoretical model of consumer demand and link formation is provided to rationalize these findings.

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Chapter 1

Location Restrictions and Resident Externalities: Evidence from the Washington State Recreational Cannabis Industry

1.1 Introduction

Amenity provision and regulation are perennial topics of discussion in state and local governments due to their highly polarizing nature. Disagreements in amenity provision policies occur due to disagreements between consumers that perceive gains from access to an amenity versus the potential localized impact that the amenity may impose on residents. In order to satisfy very heterogeneous goals while providing desirable services such as providing affordable housing or allowing Airbnb to operate [1], policymakers often enact zoning and various other land-use regulations. These regulations in turn may affect firms, who make strategic decisions when their environment changes, which may affect the degree of amenity provision. Understanding how firms may react to regulations before enacting them is crucial for devising sound policy and avoiding unintended consequences. At the same time, oftentimes, jurisdictions that are influenced by private parties or public opinion may pursue certain policies that are enacted in the name of a noble goal but with the implicit objective to achieve a different goal, which raises the question on the optimal way to devise policy. In this paper, I investigate these questions and study the impact of various land-use regulations around sensitive-use areas and other restrictions on the recently legal Washington State recreational cannabis industry and its effects on the welfare of consumers and residents, and

[1] For example, Airbnb is often banned in areas zoned for residential use.

on tax revenues.

The cannabis industry is a canonical example of an amenity that a substantial percentage of the populace believes should be provided in some form [2], but many, even among its supporters, are against having a cannabis firm in their neighborhoods [3] [4]. Cannabis and its consumers, like other illicit drugs, have traditionally been associated by society and popular culture with crime, marginalization, and poverty, and a large fraction of households are against anything involving cannabis and its allegedly crime-inducing factors that may alter their neighborhood character. To this end, Washington State's referendum included location restrictions that forbade cannabis firms from locating nearby sensitive-use areas such as schools, public parks, child care centers, etc. In practice, the restrictions meant that firms were heavily constrained regarding their location choices, which led to substantial clustering. In a standard model of spatial competition, clustering may lead to intensified price competition, which may attract more demand. Whereas the main goals of the regulators and referendum drafters were to maximize tax revenues while minimizing cannabis consumption and reducing exposure of cannabis to minors, the actual effect may have been more about protecting property values for residents and encouraging consumption through lower prices and an easy consumer experience [5]. The natural questions that arise from this setting are whether these regulations had the intended goals, what the welfare impact of relaxing location restrictions would be, and how each interested party is impacted.

In this paper I answer these questions in a twofold manner. First, I show reduced-form evidence that cannabis dispensaries act as a disamenity when they locate near homes

[2] Pew Research Center, about two thirds were in favor of some form of legalization in 2019, https://www.pewresearch.org/fact-tank/2019/11/14/americans-support-marijuana-legalization/

[3] Roughly 70 percent of parents do not want cannabis dispensaries near their schools https://www.studyfinds.org/kids-cannabis-majority-of-parents-say-dispensaries-should-not-be-near-schools/

[4] Roughly 41 percent of survey respondents would feel negatively affected if a cannabis retailer entered in their neighborhood https://www.pewresearch.org/politics/2015/04/14/in-debate-over-legalizing-marijuana-disagreement-over-drugs-dangers/.

[5] Relative to the black market, which traditionally involved finding suppliers through word-of-mouth.

and near schools, the main sensitive-use area of interest. I also show reduced-form evidence of intensified price competition when firms locate closer to each other, partly due to the stringent location restrictions. Motivated by these empirical findings and to formalize the endogenous response of location restrictions on market outcomes and welfare, I develop a structural model of consumer demand and firm entry and location. The model takes the location restrictions as constraints on where firms may locate their businesses, which affects their profitability due to being potentially farther away from consumers and more clustered together with other firms. I estimate the model using comprehensive data covering the entire supply chain of the industry. Finally, I conduct counterfactual land-use policies that relax the location restrictions around sensitive-use areas, giving firms more options to locate but also potentially being closer to sensitive areas.

The reduced-form analyses consist of two parts: the market and the residents. First, I show that almost half of sales occur in firms that have a very geographically near competitor, and that prices are lower relative to having a competitor farther away through various distance specifications. Each month, new entrants update the distance to the closest competitor, providing additional variation in price competition. Second, I use a lottery for allocating licenses as plausibly exogenous variation to show that cannabis retailers locating near homes and near homes' assigned schools leads to lower property values for properties sold once the market begins. While I find economically and statistically significant effects for both channels, the effect is larger then retailers locate near a school, which is consistent with the goals of the location restrictions.

In the model, firms first decide whether to apply for a license in a jurisdiction. Due to license caps, they are not guaranteed to obtain a license if there are more applicants than licenses. Firms that obtain a license, knowing about the consumer demand, play a sequential location decision game by choosing locations among the available areas left after the location restrictions and existing zoning regulations. Upon deciding upon locations, firms set prices. Finally, consumers choose between nearby stores and purchase a product in the framework of a nested-logit model with travel costs. Demand parameters are estimated following the generalized method of moments estimator outlined in Berry, Levinsohn and Pakes (1995), location-specific fixed costs from the location decision game are estimated via method of simulated moments, and the sunk costs from the application game are estimated via maximum likelihood. The estimation procedure involves computing variable profits for firms in each jurisdiction for all possible location configurations, which provides the payoffs for all the nodes in the sequential location decision game. To ensure the estimation is computationally feasible, I divide large jurisdictions into location sets, ensuring that no strategic geographical area for firms contains more than 3 firms and 20 locations [6]. In the application stage, firms apply if expected profits are non-negative: note that profits are in expectation since they are not guaranteed to receive a license in the case of binding license constraints. Because of this wrinkle, sunk costs are estimated even for those firms that do not obtain a license, and thus more closely resemble the opportunity cost of entering the market rather than licensed firms' operating fixed costs.

I find that relaxing location restrictions around sensitive-use areas down to 100 feet increases consumer surplus by 80 percent in the entire state and by 57 percent in King County, increases quantity sold and subsequently, firm profits by 87 percent and 52 percent, increases sales tax revenue from the market, exacerbates homeowners' negative externality by 8 percent in King County, and reduces property tax revenue, but on net, there are resident and tax revenue improvements relative to the baseline policy. On the resident side, residents perceive a net surplus due to a combination of factors: in King County, stores locate in denser areas, reaching more consumers at a lower travel cost, which increases consumer surplus. Consumers appear to be sensitive to travel costs while being fairly price inelastic,

[6] I allow some location sets to contain more than 3 firms and allow other sets to contain more than 20 locations, but not both.

so any increase in prices from firms locating farther from each other and exercising market power is not felt as strongly as if firms were farther away from consumers. Homeowners are more negatively impacted but not by enough to offset the gains that consumers perceive due to the additional number of available houses between 1000 ft and 100 ft, and the prices in these affected areas. Also, some new sets of properties are impacted due to stores locating close to their assigned schools, but old sets of properties end up not being affected through that channel due to firms changing locations. License caps in binding jurisdictions help mitigate the externality that would be imposed on residents through limiting the number of stores that can enter the market and be near schools. While more properties are impacted than in the baseline, the additional number does not translate to losses larger than the consumer surplus increase. Because sales and property taxes closely track firm profits and property values, respectively, the qualitative pattern for resident surplus is replicated for tax revenue collection.

My findings indicate that, depending on the social planner's objectives, state and local governments can allow less stringent location restrictions for businesses than what are currently imposed without facing a net welfare or tax revenue loss. The implications from this paper not only apply to states that have already designed their cannabis markets or are in the process of doing so, but to any policy that may have localized impacts and employs land-use regulations to mitigate potential negative externalities.

1.2 Related Literature

By exploring the welfare impact of land-use regulations for the Washington State cannabis industry, I make several contributions to the existing literature. First, I show reduced-form causal evidence of cannabis retailers acting as disamenities when locating near properties' assigned schools and other sensitive-use areas. Second, I assemble geospatial data to recreate the spatial constraints that firms face in this market. Third, I develop a tractable model appropriate for modeling firms' decisions in the presence of license and location constraints and estimate it with comprehensive data on the industry's supply chain. Lastly, I study the role of various regulations on the welfare of different types of agents present in the market, using location as a novel dimension to study the regulation of sin good markets.

1.2.1 Spatial Differentiation

I contribute to a long line of literature in spatial differentiation. While seminal papers like Hotelling (1929) used the idea of distance as an analogy to explain competition between firms along a horizontal beach, recent papers such as Davis (2006) and Holmes (2011) have exploited the actual spatial nature of demand to better incorporate how distance affects consumption and substitution patterns. I follow these papers in adding distance as a disutility term in consumers' utility function. I also follow a slightly different literature in empirical industrial organization that incorporates firms' location decisions as a strategic variable, starting with Seim (2006) who studied video-rental stores, and later refining the role of spatial differentiation in papers such as Zhu and Singh (2009), Datta and Sudhir (2012), and Orhun (2012). Whereas Datta and Sudhir (2012) examines the role of zoning restrictions on product-type stores, I examine the role of a different type of restriction in spatial differentiation on different market outcomes, namely welfare measures for consumers, residents, and tax revenues. A common limitation in most papers that study location decisions is the lack of detailed demand-side data, which I am able to exploit thanks to comprehensive data on my industry's entire supply chain.

Other relevant strands of this literature study spatial competition and its role on preemptive entry such as Zheng (2020), the costs of zoning regulation for convenience stores in Nishida (2014), and efficient firm location configurations in the restaurant industry in Sedov (2020). In my setting, license restrictions make concerns about preemptive entry relatively unimportant due to the fact that firms can apply for a modest sum and if the license cap binds, the licenses are allocated via lottery. This means that the market is regulated in a way that there is no way firms can enter before others and thus preempt entry of rivals. However, being the first firm to locate in a desirable location may lead other licensed firms to potentially change their locations, which may suggest the presence of a first-mover advantage. In addition, restrictions on where firms can locate may lead to suboptimal entry from an efficiency standpoint. Regarding policy evaluation, I measure both a variety of benefits and costs from relaxing land-use regulations for a given market, as well as modeling firms' entry and location decisions while ensuring the model remains computationally feasible.

1.2.2 Models of Firm Entry

I also contribute to the industrial organization literature on models of firm entry. My entry model incorporates license caps when firms are considering whether or not to apply for the market in a given jurisdiction, and if we let the number of licenses go to infinity, the model collapses to the classic Bresnahan and Reiss (1991) entry model. The most similar paper to my firm entry modeling is Schaumans and Verboven (2008), where they model pharmacy entry decisions under entry restrictions. I follow their steps in endogenously modeling the outcome of whether a cap is binding or nonbinding. Whereas they are concerned about the impact of the license restriction on welfare, I am more concerned about the impact of the location restrictions, and the license restrictions in my setting are just another institutional feature that I account for. A point of distinction between my model and Thomas (2019) is that she models this market's firms' entry decisions by ex post dividing jurisdictions into binding and nonbinding groups and obtains set identification of the fixed costs via a moment inequality method, whereas I allow the binding/nonbinding outcome to be an endogenous result of firms playing the entry game and estimate the point identified sunk costs for all applicants, even those that do not obtain a license, via maximum likelihood.

1.2.3 Regulation of Sin Goods

Another major strand of literature I contribute to is on regulation of so-called sin goods. Due to data availability and legal reasons, the bulk of the literature has focused on alcohol and tobacco. Similar papers about alcohol markets like Seim and Waldfogel (2013) and Miravete, Seim and Thurk (2018) study questions of efficiency, such as should a state control all liquor stores, and taxation, like are taxes too high or too low and the heterogeneous impact on consumers, respectively. This project tackles questions that arise when a state allows the private sector to create a new market, under heavy regulations of entry, location, and taxation. A more nascent literature on cannabis markets has spawned in the recent years, with Thomas (2019) studying questions of allocative inefficiency, and Hollenbeck and Uetake (2021) on questions of taxation. To my knowledge, this is the first paper to look at how certain location restrictions that were aimed to protect the public, especially minors, affect the market structure and in turn, affect welfare in a variety of ways.

1.2.4 Externalities

A third major strand relates to externalities. A cornerstone of economics, starting in recent history of economic thought with John Stuart Mill and Henry Sidgwick [7], formalized by Pigou (1921), who brought externalities into the mainstream, and conceptually refined by Coase (1960) through the lens of legal disputes under transaction costs, who spurred an entire literature in both economics and in law [8], deals with the deceptively simple idea that an action that brings benefits to some may have potentially unexpected effects on others who did not choose to engage in this action. The literature on externalities, both theoretical and empirical, is vast. A few recent papers that measure various kinds of externalities like

[7] See Medema (2009).

[8] As well as myriad interpretations of "what Coase actually meant" (See Medema (2020)).

Greenstone, Hornbeck and Moretti (2010) and Currie et al. (2015) measure the benefits of agglomeration and the cost of living near coal plants, respectively, guide the methods in this paper. I follow Currie et al. (2015) approach to measure the potential negative externality residents perceive from having a cannabis retailer 1) near their home and 2) near their assigned school by using changes in property values as a proxy for residents' preferences.

1.2.5 Land-Use Regulation

One interesting and under-explored intersection of literatures is the one concerning industrial organization and land-use regulation, as the decision of where to locate can be crucial for businesses. This intersection is fairly sparse due to the manifold data limitations and myriad regulations: zoning data is usually at the county level or at the city level, firms may operate at a broader scope and we might need data from a specific industry, and it is not clear if an industry is affected just by the regular zoning regulations or by additional policies which may vary by the industry [9]. Outside the intersection, work such as Turner, Haughwout and van der Klaauw (2014) measure the welfare impact of land-use regulations by measuring causal effects through cross-border changes in land development. Papers similar to the spirit of this project are Ridley, Sloan and Song (2010), who show through a theoretical model and survey data the potential anti-competitive effects of retail zoning and Suzuki (2013), who shows that more stringent zoning regulations in Texas increases barriers to entry for hotels. I contribute to the literature about land-use regulation and zoning by showing that making land-use regulation more restrictive has significant impacts on market structure, which in turn affects consumer welfare and taxation. One specific example of this contribution is local governments imposing location restrictions around sensitive-use areas, which act as an additional regulation on top of the usual zoning layers. Usually, those in charge of

[9] For example, cement plants will usually be located in areas zoned for industrial use, convenience stores will usually be located in areas zoned for commercial use, and so on.

drafting these regulations tend to ignore or minimize any potential market structure related consequences.

1.2.6 Amenity Valuation

Lastly, I contribute to the long literature in urban economics of amenity valuation, endogenous amenities, and land-use regulation. Some recent, similar papers like Black (1999) use a boundary discontinuity research design to measure whether parents value better schools. Bajari and Kahn (2005) use hedonic methods to estimate the value of certain (dis)amenities like climate or commuting. Bayer, Ferreira and McMillan (2007) uses a discrete-choice model to estimate residents' valuation of schools and neighborhoods, and Currie et al. (2015) uses a natural experiment and the 'ring method' to measure the disamenity , through property values, of building a power plant close to properties. Thomas and Tian (2019) apply Currie et al. (2015)'s method for my setting, and find that cannabis retailers locating near properties has an economically significant negative effect on property values. I expand their method by showing evidence of a second channel, that property values also decrease when a property's assigned school, either elementary or high school, has a cannabis retailer locate near it, and build a model around this result. A recent paper that is similar in spirit is Almagro and Dominguez-Lino (2020), where they study the role of endogenous amenities, in their case Airbnb, in shaping the location sorting decisions of residents. They show heterogeneity in the valuation of having Airbnb near their residence, and apply these mechanisms to questions related to zoning and price/quantity regulations in housing markets. I study a similar phenomenon for an amenity that exhibits large heterogeneity in its valuation among residents and examine the impact of its respective zoning/land-use regulations on welfare outcomes.

The paper is structured as the following roadmap: Section 3 describes the necessary institutional background of the Washington State cannabis industry and the relevant regulatory features. Section 4 describes the data used. Section 5 consists of reduced-form analyses that show evidence of the impact of location restrictions on market structure and externality mitigation. Section 6 describes the model. Section 7 explains the estimation strategy. Section 8 goes over the results of the model's estimation. Sections 9 and 10 explain the counterfactual policy scenario and its results, and Section 11 concludes.

1.3 Institutional Background

As of 2020, cannabis remains a Schedule I drug at the federal level since President Nixon signed the Controlled Substance Act in 1970, meaning that it has "no currently accepted medical use and a high potential for abuse" (DEA, 2020). In 2013, the Department of Justice issued a list of recommendations known as the 'Cole memo', outlining the possible course of action that states could take to avoid federal crackdown in the event of state-level cannabis legalization. Among these suggestions were policies such as not letting product be diverted into illegal states, prevent cannabis consumption by minors, and prevent drug money flow to cartels. As of today, recreational legal cannabis is a $9 billion industry and generates almost $2 billion of tax revenue.

1.3.1 I-502 Referendum

In November 2012, Washington State residents voted in favor of Initiative 502 (I-502), which allowed the production, sales, and taxation of recreational cannabis goods for 21+ adults. The referendum outlined the market structure, the supply chain regulations, the kinds of advertising allowed, the license system and the location restrictions for firms, among a few. The Washington State Liquor Control Board would take on the regulation duties of the cannabis market and cities could impose additional regulations if their residents desired.

The industry's regulatory environment was inspired by the alcohol industry's vertically disintegrated supply chain's market structure, where producers for the most part can't sell directly to consumers [10]. Firms could apply to become producers, processors, and/or retailers. Producers grow the plant either indoors in greenhouses or outdoors. Processors process the plant into the final product, which can range from placing the product into the appropriate packaging, extracting the chemicals and placing it into vaporizer cartridges, or preparing liquid or solid edible products. Retailers sell the products to consumers in commercial stores. If a firm applied to be a producer or a processor, it could not apply to be a retailer. Producers could also apply to be processors, and due to the ability to create their own brand, the upstream of this market is highly vertically integrated. Firms that applied for retailer licenses could potentially obtain up to 3 licenses statewide. This means that there exist some chains. However, the chain business model is not yet very developed: the existing chains, while being owned by the same person, are managed by different people and obtain their inventory and form relationships with producers independently.

The referendum also implemented an excise tax. At the beginning, it mandated a 25% tax at each step of the supply chain but in mid-2015, it was changed to a 37% tax at the point-of-sale level. Currently, Washington state has the highest excise tax on cannabis out of all the legal states in the US [11].

[10] In virtually all states in the United States, liquor producers coordinate with distributors who transport liquor to liquor stores. In theory, distributors are independent third-parties but recently, producers have been able to use their own distribution companies and shut out smaller competitors from access to retailers nationwide. See U.S. v. Anheuser-Busch InBev SA/NV and SABMiller plc. Up until 2016, Washington state producers and retailers had to transport their own product from the grow facility to the retail stores. After 2016, the regulator started issuing licenses for transporters, serving the same function as distributors in the liquor industry but with more stringent tracking regulations.

[11] Hansen, Miller and Weber (2020) study the impact of this reform on the degree of vertical integration at the upstream level and on taxation. Hollenbeck and Uetake (2021) study the optimal tax policy for this market, finding that taxes are to the left of the Laffer curve and can thus admit higher taxes without losing tax revenue.

1.3.2 Background on Firms and Licenses

About 85 percent of producers are integrated with processors. Based on the proportion of integrated producers/processors and the observed sorting patterns between producer to processor, it is safe to say that the processor stage is mostly cosmetic and does not make strategic decisions in this market. The firms that appear to make strategic decisions are the producers, who must decide how much product to grow and where they will sell it, and the retailers, who must decide who to buy the product from and sell it to consumers at a reasonable markup. Washington State had between 600-700 producers during the 2015-2016 period, more than three times the number of retailers in July 2015, and this number swelled to more than 1000 active producers by mid-2018. The main difference between producer and retailer licenses is that the producer application license window was closed in December 2013 and, to my knowledge and unlike the retailer application window, was never reopened. Thus, any firm that applied to be a producer before the application window closed and got its application approved could enter, unlike retailers who are subject to a license cap.

1.3.3 Location Restrictions

I-502 forbade applicants from locating within 1000 feet from elementary, middle, or high schools, playgrounds, libraries, child care centers, public parks, public transit centers, or arcades. Figures 1 and 2 show maps of Seattle with the existing location restrictions at 1000 feet on the left-hand side, and a map of Seattle if those restrictions were to be lowered to 100 feet. The purple areas are where cannabis firms could locate and the grey areas are where they were barred from locating. Note that in the right-hand image, a significant amount of nonallowed locations remains. This is due to the existing zoning regulations for commercial enterprises [12].

[12] One could think of the right-hand map as all the locations where convenience stores such as 7/11's could locate, and the left-hand map represents the additional location restrictions for cannabis firms.

When applying for a license, potential firms had to submit a proposed location that complied with I-502's location restrictions, as well as the existing zoning regulations for commercial enterprises. The initiative also allowed jurisdictions to relax these requirements if they desired. In practice, some jurisdictions relaxed some of these upon realizing that there was no space for retailers to locate [13]. Retailers report finding a location that complied with the stringent location restrictions among the key difficulties when considering entering the market. The other difficulty in finding a location was not being able to secure a lease from retail spaces currently being paid through a mortgage given by a bank, since banks refused or were unable to do business with cannabis firms due to the opaque nature of the legality. In practice, firms secured retail space leases from private parties or built their own retail stores from scratch [14].

Firms that applied to become producers and/or processors were not subject to any license caps and were easily awarded a license if the paperwork was correct. Producers and processors were also subject to location restrictions but since producers were mostly on rural land and on private property, very few were affected by this constraint.

1.3.4 Dispersal Restrictions

Jurisdictions and residents were concerned about the potential impact of having a retailer in a location on crime, neighborhood feel, and the kind of people that frequented the area. Seattle, for example, did not want to create a cannabis-specific district so it mandated that no more than two retailers would be allowed within 1000 feet of each other. In practice, this policy spread out the firms across the map but some firm clustering remained, in sets of two, due to the significant location restrictions. Other jurisdictions' existing zoning regulations effectively designated certain urban districts as the only areas where commer-

[13] The case for relaxing location restrictions and up to what extent are discussed in detail in town hall records from various local jurisdictions.

[14] I indirectly address firms' inability of securing leases through banks when modeling location decisions.

cial enterprises could locate, effectively opening the door to cannabis business districts, the opposite effect of dispersal restrictions policies.

1.3.5 Licenses and Lottery

In this project I focus on the strategic decision of firms entering a market with license and location restrictions. The state had restricted the number of available retailer licenses in each jurisdictions based on a commissioned market study. Figure 3 shows the available number of licenses in King County. The total number of available licenses in the state was 334, with the greatest number allowed for a jurisdiction was 21 for the city of Seattle. There was also a cap on licenses for each county at large, which was meant for 1) firms that wanted to locate in unincorporated parts of the county. If more firms applied for licenses than the quota, the state would run a lottery and select the winners randomly. About 70% of the applicants that received a license entered. If a firm that received a license was unable to enter for some reason, the state would transfer this license to the next applicant on the lottery results. Every Tuesday during the 30-day window of November 2013, the information of potential firms that applied was uploaded to a spreadsheet on the WLCB website, so firms considering applying knew about their potential competitors to some extent [15].

In early 2016, the state decided to merge the medical and recreational markets. Some differences between the two markets stem from the fact that the medical market was mostly unregulated: dispensaries could grow their own product, chemical testing was not widespread, and product quality varied widely across dispensaries. Anybody with a recreational license could apply and immediately obtain a medical license. The state also increased the number of available licenses from 334 to 556 after a market study. Unlike the first batch of licenses, this second batch was not subject to a lottery and was subject to the

[15] Potential participants knew this in theory. In practice, none of the industry participants I interviewed reported knowing about this information when applying. Instead, they knew about other potential competitors through word-of-mouth and due to previous experience in the medical market.

Figure 1.1: Available Licenses in King County

Jurisdiction	Allotments
King County	
At Large	11
Auburn (part)	2
Bellevue	4
Burien	1
Des Moines	1
Federal Way	3
Issaquah	1
Kent	3
Kirkland	2
Maple Valley	1
Mercer Island	1
Redmond	2
Renton	3
Sammamish	1
SeaTac	1
Seattle*	21
Shoreline	2
Tukwila	1

WLCB's discretion. Priority was given to applicants from the November 2013 application period that did not obtain a license as well as existing medical dispensaries. This measure led to several medical dispensaries closing without a clear course of action. The recreational cannabis producers took on the duty of growing medical-grade products to sell to medically licensed retailers.

1.3.6 Financing Issues

Due to the illegal status of the product at the federal level and given banks' operation across state lines, industry business owners were not able to obtain credit from banks to open their businesses, and were not able to secure retail space that was being paid off by a mortgage through a bank. The first point meant that potential firms had to obtain start-up costs by themselves or through private lending. The second point meant that they could only open up a shop in retail space that was either fully paid off and managed by private individuals, or on undeveloped space, which would require to create a store from scratch and thus greater than usual sunk costs. As the market matured, firms in Washington State were able to open bank accounts in certain credit unions, but their access to financial services remains heavily restricted.

1.4 Data

My main sources of data include cannabis retail sales, inventory transfers between firms, laboratory sample potency results, and lottery license results from the Washington Liquor and Cannabis Board, and property sales from the King County Tax Assessor. I also use additional data sources to include information on consumer demographics, resident demographics, and sensitive-use area locations.

1.4.1 WLCB Traceability Data

The WLCB Traceability data consists of three main datasets: inventory transfers, laboratory sample potency results, and retail scanner data. Inventory transfers consists of inventory sent from producers to processors, processors to retailers, and producer/processors to laboratories. The transfer data includes the date the inventory was sent, when it was received, wholesale price, inventory type, inventory description, strain, and weight. The transfers data can be linked to lab results data, which includes information on THC and CBD potency of products. Lastly, there is retail-level scanner data, which features sales date, sales price, weight, and product description. One of the unique features of the retail scanner data is that it is a complete dataset of all sales for an entire market [16]. These three datasets can be linked by an inventory ID. There is a unique inventory ID for each 'lot', a standard unit of production.

I aggregate products up to product categories and focus on the top 4 types which account for 96.5% of sales: usables, inhalables, solid edibles, and liquid edibles. A product is a product category-retailer-month. I compute the median and average THC and CBD percentages of these aggregated products. Since usables vary by weight, I standardize them to 1 gram units and compute the corresponding weighted average prices. The other products are already at a unit-equivalent. Inhalables tend to be the priciest products both in terms of sale and wholesale price, as well as chemical potency. Edibles have low potency and their main variation is due to weight and flavors. Usables vary substantially in potency and chemicals, mostly due to differences in strain types. In addition, for each product, I compute the number of strains and number of products that the retailer offers. For example, a retailer

[16] The closest analogue is Miravete, Seim and Thurk (2018)'s Pennsylvania Liquor Control Board data on store-level purchases. Another well-known analogue is the Nielsen scanner data, which includes all point-of-sale records from a representative sample of stores across the nation. The trade-off between my data and the Nielsen data is Nielsen collects more data but contains less identifying information about the stores and the products.

can offer 5 kinds of different strains and 15 different versions (brands, sizes (if loose), type (preroll, flower, etc)) of usables in a given month.

1.4.2 Retailer license lottery results

The WLCB collected data on applicants for each jurisdiction: upon submitting an application, they had to provide a proposed location. This location was not binding, but if they received a license and wanted to locate elsewhere, they had to fill a form and pay $75. In practice, the location restrictions greatly limited the number of possible places firms could open an establishment, so about 50% of lottery winners located exactly where they had applied and an additional 25% located within a third of a mile from their proposed location. After the 30-day window closed, Washington State University conducted a lottery for those jurisdictions where the license cap was binding. Applicants were given a number and if the number was smaller than the allowed number (e.g a firm received the number 3 in a jurisdiction with a cap of 5), they were awarded a retailer license. Unlike retailers, producers and processor licenses were freely awarded.

1.4.3 King County property sales data

I use property sales data from 2014 until 2017 to examine the role of retailer proximity as a disamenity to residents. This sales data includes property characteristics such as the number of bedrooms, bathrooms, square feet, a condition variable assigned by the County, building type, and the zoning designation of the neighborhood.

1.4.4 Census data

I use data from the 2010 Census to incorporate information about consumers. I assume consumers live in the population-weighted census tract centroid. For each census tract centroid, I calculate the distance to the three nearest retailers. I also merge these centroids with demographic data from the 2014 American Community Survey. I calculate the percentage of people over 21 years old and the population density of each census tract.

In addition, I use the Census data's rich information on neighborhood characteristics and the demographics of residents to complement the property sales data. This helps account for potential heterogeneity in resident valuation: it may be the case that some residents view having a retailer nearby as a significant disamenity, while others would welcome its presence. I include demographic characteristics into the reduced-form hedonic analyses to more accurately measure residents' willingness to pay.

1.4.5 Zoning layers

In order to determine which locations are off-limits for retailers, I collect the zoning layers from all counties in Washington state. I use the shapefiles from the Puget Sound Mapping Project, which includes the entire zoning layers of Whatcom, Skagit, Snohomish, King, San Juan, Clallam, Jefferson, Kitsap, Mason, Thurston, and Pierce counties. For those jurisdictions that I was unable to obtain shapefiles, I collected zoning maps from each city's website and created the appropriate zoning shapefile in ArcMap. These shapefiles allow me to drop all census tracts that are mostly in residential zoning and other areas where commercial spaces are not allowed to locate. To determine which locations remain available for retailers, I create buffers around sensitive-use areas and drop all census tracts that are mostly covered by the buffers, leaving those with a substantial percentage of area available for setting up a store.

1.4.6 Sensitive-use area locations

I collect the locations of all restricted entities included in the I-502 and create buffers of 1000 and 100 feet around each location. These locations are crucial in order to assign properties to nearby SUAs and to determine whether a location is feasible for the firm problem. The buffers show the ubiquity of the restriction. Figures 1 and 2 show the location restrictions in Seattle suggested by the i-502 referendum, 1000 feet, and how the restrictions would look like if they were reduced down to 100 feet. In the two figures, the pink areas are available mixed-use/commercial zones where retail establishments can locate. The grey areas that stay constant across the two figures are residential areas where no retail establishment can locate. The grey areas that change as I change the buffer size are the areas in mixed-use/commercial zones that become available for retailers.

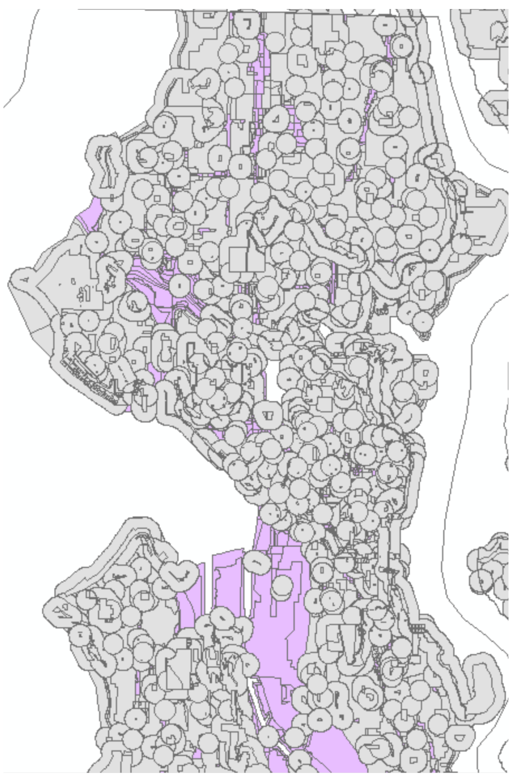


Figure 1.2: Seattle with 1000 ft location restrictions

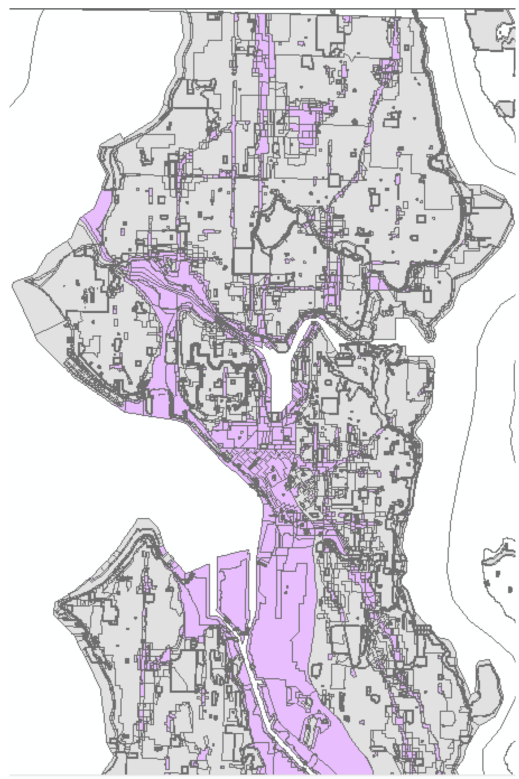


Figure 1.3: Seattle with 100 ft location restrictions

1.5 Reduced-Form Analysis

I present reduced-form evidence that 1) the location restrictions restricted the locations where retailers could locate, leading to intensified price competition and 2) using changes in property values as a proxy for residents' preferences, retailers locating close to homes and their assigned schools negatively affect property values.

1.5.1 Competitor Proximity on Prices

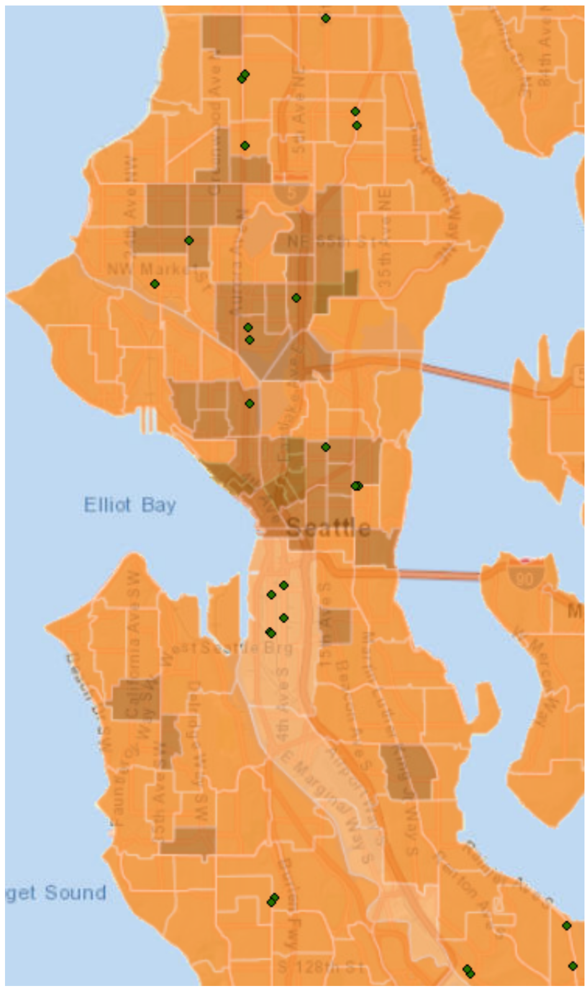
To motivate the claim that firms were affected by the location restrictions, Figure 4 shows a map of where firms have chosen to locate in Seattle. Firms locate very close to each other, in a way that is reminiscent of gas stations. Table 1 provides summary statistics of the proximity of stores, first by looking by retailers and second by sales. These summary statistics show that a significant amount of economic activity in this market occurs through firms that have a competitor very close by, potentially affecting price and product choices. For example, first, we can observe that even though the percentage of retailers that have a nearby competitor - which means within 1.5 km - is 40 percent, they account for 50 percent of sales. Second, the table shows that 6.7 percent of retailers have a nearby competitor within 100 meters, about the length of a standard city block.

Table 1.1: Summary Statistics: Distance to Nearest Competitor

Distance to nearest competitor	% By Sales	% By Store
<0.1km	9.84	6.67
0.1-0.3km	15.46	10.48
0.3-0.5km	8.01	9.52
0.5-1.5km	15.78	14.29
>1.5km	50.91	59.05

I run regressions of retail price on competitor proximity to test the hypothesis that having a nearby competitor leads to lower prices. I control for product characteristics such as brand, weight, description, city, producer brand, strain, month, and inventory type. I also change the distance measures of how close a firm is to a nearby competitor each month

Figure 1.4: Retailers in Seattle, 2016



as new firms enter the market. The goal is that the only variation left affecting prices is the role of competitor proximity.

Table 2 shows that when we regress the distance to the closest competitor on logged sales price, increasing the distance by 1 km is associated with 20.3 percent increases in sales price. When I regress the distance to the closest competitor on the logged margin, increasing the distance by 1 km is associated with 16 percent increased in the margin. The fact that both effects are similar implies that most of the increase is due to retailer market power and not due to the wholesale price. However, the main issue with this kind of analysis is that the distance effect rapidly disappears as distance increases.

Table 1.2: Retailer Proximity on Price Competition, Continuous Distance

	Log(Price)	Log(Margin)
	(1)	(2)
Distance To Closest Competitor	.203	.161
	(.015)***	(.006)***
Retailer Age	.050	.015
	(.001)***	(.0005)***
N	1220183	1212883
R^2	.302	.218

This table presents regression estimates of the effect that the distance of the closest competitor, in kilometers, that each retailer has on retail prices and on margins, both logged. Robust standard errors are in parentheses.

For more granular interpretation of the competitor proximity effects on price, Tables 3 and 4 show the effects if we break down the proximity in distance bins. I break down distance into five discrete bins: within 100 meters, between 100 meters and 300 meters, between 300 meters and 500 meters, between 500 meters and 1500 meters, and above 1500 meters. Table 3 shows the results when we use city as a fixed effect and Table 4 shows the results when we use the 3-digit zipcode as a fixed effect. The city-level specification is preferred since it accounts more realistically for the local competition features of the market,

Table 1.3: Retailer Proximity on Price Competition, Distance Bins, City FE

	Log(Price)	Log(Margin)
	(1)	(2)
Within 0.1km	-.050	.006
	(.003)***	(.001)***
Between 0.1km & 0.3km	-.022	-.053
	(.003)***	(.001)***
Between 0.3km & 0.5km	-.066	-.057
	(.004)***	(.001)***
Between 0.5km & 1.5km	-.052	-.00008
	(.003)***	(.001)
Retailer Age	.019	.001
	(.0003)***	(.0001)***
N	1220184	1212884
R^2	.282	.185

This table presents regression estimates of the effect of competitor distance on retail prices and margins, logged. I construct discrete distance bins around each retailer, and assign a 1 if a retailer has a competitor in each distance bin and 0 otherwise. I include city-level fixed effects. Robust standard errors are in parentheses.

Table 1.4: Retailer Proximity on Price Competition, Distance Bins, Zip3 FE

	Log(Price)	Log(Margin)
	(1)	(2)
Within 0.1km	-.067	.010
	(.003)***	(.0009)***
Between 0.1km & 0.3km	-.005	-.044
	(.002)**	(.001)***
Between 0.3km & 0.5km	-.043	-.040
	(.003)***	(.001)***
Between 0.5km & 1.5km	-.044	-.005
	(.002)***	(.0009)***
Retailer Age	.017	.0003
	(.0002)***	(.00009)***
N	1220185	1212885
R^2	.261	.155

This table presents regression estimates of the effect of competitor distance on retail prices and margins, logged. I construct discrete distance bins around each retailer, and assign a 1 if a retailer has a competitor in each distance bin and 0 otherwise. I include Zip3-level fixed effects. Robust standard errors are in parentheses.

but the patterns also hold when we use a 3-level zipcode fixed effect, which matches the rural/urban divide of the market.

The regressions are of the form:

$$log(P_{cit}) = \gamma MinDist_i + X_{cit}\beta + FE + \epsilon_{cit} \tag{1.1}$$

$$log(P_{cit}) = DistBin_i\gamma + X_{cit}\beta + FE + \epsilon_{cit} \tag{1.2}$$

where P_{cit} is either logged sales price or logged margin [17] of product c in retailer i in month t, $MinDist_i$ is the distance in kilometers of a retailer i with its closest competitor, $DistBin_i$ is a collection of distance bins for retailer i, X_{cit} includes product-level THC and CBD potency, weight, and retailer age in months. Fixed effects include producer brand, product strain, month-year, product category, and retailer zipcode.

The minimum distance and distance bin specifications show negative impacts on price at all distance bin levels, meaning that having a competitor within 1500 meters is associated with having lower prices after we control for a variety of factors.

1.5.2 Externality on Residents

The location restrictions around sensitive-use areas for cannabis retailers were arguably put in place to prevent minors from being exposed to cannabis near the places they tend to congregate. To test whether the presence of cannabis establishments has a negative impact on residents and their children, I use changes in property values for the homes that sold during the period the market started as a proxy for residents' preferences. I show that property values of homes fall when retailers locate 1) close to a property and 2) close to the property's assigned elementary/high school. Retailers locating close to a property would

[17] I use the observed retail and wholesale prices to compute the margin $\frac{P-MC}{P}$.

occur regardless of the regulation in place short of banning the cannabis market, and it can be inferred that the more important channel for regulation purposes is the one where firms locate near sensitive-use areas. For homeowner associations, residents that view housing as an investment and care about how urban amenities affect a neighborhood's feel, and for families with children, both channels may be important.

I follow a hedonic approach. First, I geocode all properties that were sold in King County between August 2014 and January 2016. I match each property to its assigned elementary/high school based on school proximity or based on school attendance zone. I also include property and neighborhood characteristics from the property sales data, the HMDA data, and from the ACS data at the census tract level. I match properties and their assigned schools to their nearest retailer that entered the market. I create discrete 'bins' based on distance from the retailer to the house and from retailers to the schools: close, medium, and far. The first bin includes all datapoints that are less than the 25 percentile in the distance. The second bin includes datapoints between the 25 and 75 percentile in distance. The third bin includes datapoints above the 75 percentile in distance. To control for the potential endogeneity of retailers locating in locations with lower property values, I include as a control variable the proximity of those applicants that did not get a license in the lottery. Figure 5 shows a sketch of the exogenous variation that the lottery provides. The proximity of a retailer to the home and to the home's assigned school is considered a (dis)amenity, which means I expect negative effects on property values. Table 5 displays summary statistics of property prices and characteristics depending on their proximity to lottery entrants and losers. Note that the sale prices for properties near entrants and near losers and quantitatively similar, whereas they are markedly different than those properties far from where potential firms applied. Table 6 displays the number of applicants and entrants in both King County and statewide. Most firms that received a license in binding jurisdictions entered their respective markets.

Figure 1.5: Exogenous Variation Provided by the Lottery - Sketch

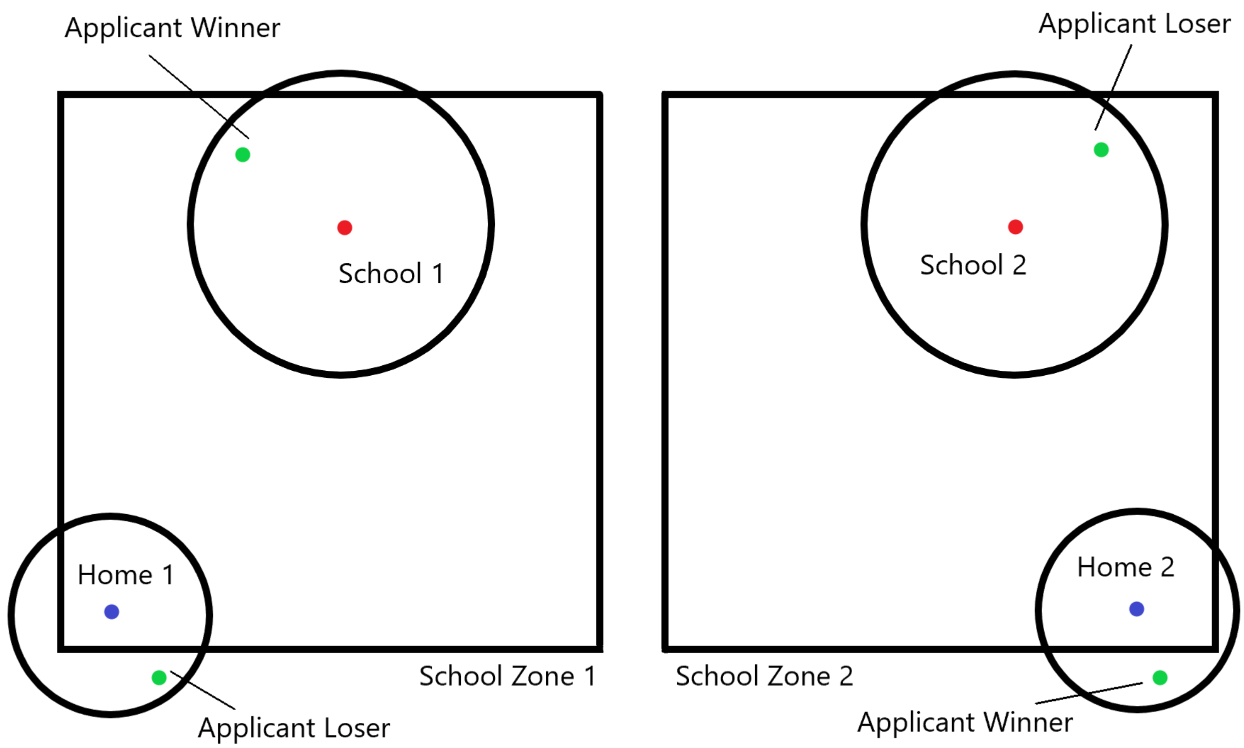


Table 1.5: Number of Applicants and Entrants

	Entrants	Winners	Losers
King County	41	47	253
WA State	216	257	868

Table 1.6: Average Summary Statistics for Properties and Demographics

Variables	All Properties	Near Entrant	Not Near Entrant	Near Loser	Not Near Loser
Sale Price ($)	579,857	459,881	605,485	481,838	613,167
Beds	3.29	3.23	3.31	3.16	3.34
Baths	1.536	1.52	1.54	1.52	1.54
Home Age	47	49.58	46.47	48.06	46.66
Sq ft	1912	1801	1936	1757	1965
Share White	70.0	68.0	70.3	75.9	68.04
$\geq$HS Grad(%)	92.73	92.92	92.96	94.86	92.01
Med Income ($)	74,551	69,858	75,553	76,278	73966
i-502 Yes %	67.87	70.04	67.43	72.37	66.4
Observations	24,669	4342	20327	6238	18,431

Hedonic regressions are of the form:

$$log(P_{ijt}) = \gamma_1 NearWin_i + \gamma_2 NearLose_i + \alpha_1 DistRetSUA_i + \alpha_2 DistRetSUALose_i + X_{ijt}\beta + FE + \epsilon_{ijt} \tag{1.3}$$

where $NearWin_i$ is a dummy variable whether the property is near a retailer applicant winner, $NearLose_i$ is a dummy variable whether the property is near a retailer applicant loser, $DistRetSUA_i$ are sets of two dummy variables (close, medium) for whether the property's assigned high school and elementary schools are near a retailer entrant, $DistRetSUALose_i$ are sets of two dummy variables (close, medium) for whether the property's assigned high school and elementary schools are near a retailer applicant loser, X_{ijt} are property characteristics like number of bedrooms, number of bathrooms, condition, age, square feet, and neighborhood characteristics like census tract demographic data and precinct-level i-502 referendum results. Fixed effects include quarter-year, property type, zoning area type, and census tract.

I repeat this exercise for the other sensitive-use areas but I find mostly null results potentially for two reasons: 1) families with children are likely the main negatively affected demographic group [18] and 2) residents have a choice of which library/park/etc to go to, but they are exogenously assigned to a specific school based on attendance boundaries. The qualitative patterns are of the expected signs (e.g. being near parks has positive coefficients) but the coefficients are not statistically or economically significant. I also repeat the exercise for churches [19], which are not in the I-502 list but may have people that do not want a

[18] Conversations with real estate agents regarding residents' preferences toward cannabis retailer proximity to sensitive-use areas confirm the qualitative pattern of results.

[19] Residents in the Central District neighborhood in Seattle protested in 2016 against the opening of a cannabis store next to a historic church that unofficially offered an afterschool program for the neighborhood's youth, even prompting a hip hop protest song: https://www.youtube.com/watch?v=LSUaa_rckaA, https://www.seattletimes.com/seattle-news/marijuana/protesters-march-on-seattles-uncle-ikes-pot-shop/

cannabis retailer next to their place of worship. I don not observe any results, probably because it is likely that people do not go to their nearest church. Without better data, I am unable to examine that matter further.

Table 7 shows the results from hedonic regressions of property characteristics and amenities on logged property sales price. The first specification creates dummies for the property being within 0.579 km from a retailer applicant loser, and being within 0.579 km from a retailer applicant winner. The second specification increases that distance up to 0.704 km for both of these dummies. I also include two dummies for the property's assigned high school and elementary school: for both sensitive-use areas, there is one dummy variable for whether the SUA is within 0.8 km of its nearest retailer, and one dummy variable for whether the SUA is between 0.8 km and 1.6 km of its nearest retailer.

Both specifications display the same qualitative patterns. Being near a retailer winner's proposed location decreases property values by about 2-2.5 percent. Being near an applicant loser's proposed location has no impact on the property's sale price. A property's assigned high school being within 0.8 km of a retailer winner has a negative coefficient (a decrease of about 2.8 percent) but is statistically insignificant. A property's assigned high school being between 0.8 km and 1.6 km of a retailer winner leads to a decrease of about 4.5 percent. A property's assigned elementary school being between 0.8 km and 1.6 km of a retailer winner leads to a decrease of about 3.7 percent. A property's assigned elementary school being between 0.8 km and 1.6 km of a retailer winner leads to a decrease of about 4.6 percent.

In Tables 8 and 9, I run specifications for 1 bin for properties and for schools, and for 2 bins for properties and 2 bins for schools, and find similar results. This battery of specifications suggests that there are two channels by which cannabis retailers negatively affect residents: first, through proximity to residents' homes and second, through proximity to residents' assigned schools.

Table 1.7: Effect of Retailer Entry on Property Values - 1 bin each

	log(Price)	Log(Price)
	(1)	(2)
[γ_1]: Home Near Retailer Winner	-.022	-.028
	(.011)**	(.010)***
[γ_2]: Home Near Retailer Loser	-.008	.005
	(.009)	(.009)
[α_1]: Retailer Winner Near HS	-.042	-.041
	(.016)**	(.016)**
[α_2]: Retailer Winner Near ES	-.049	-.049
	(.017)***	(.017)***
Retailer Near ES Loser	-.015	-.016
	(.014)	(.014)
Retailer Near HS Loser	.009	.009
	(.021)	(.021)
N	22816	22816
R^2	.567	.567

Column 1 defines 'Home Near Retailer Loser' and 'Home Near Retailer Winner' equal to 1 if the property is within 1900 ft (0.58 km) of retailer applicant losers and winners, respectively. Column 2 defines 'Home Near Retailer Loser' and 'Home Near Retailer Winner' equal to 1 if the property is within 2300 ft (0.70 km) of retailer applicant losers and winners, respectively. Robust standard errors are in parentheses.

Fixed effects: month-year, census tract, zipcode, zoning.

X_{ij}: property characteristics, precinct-level i-502 referendum results, elementary school quality, near lottery loser address for schools.
$***$: significant at 1% level. $**$: significant at 5% level.

Table 1.8: Effect of Retailer Entry on Property Values -1 bin homes, 2 bins schools

	Log(Price)	Log(Price)
	(1)	(2)
$[\gamma_1]$: Home Near Retailer Winner	-.021	-.025
	(.010)**	(.010)***
$[\gamma_2]$: Home Near Retailer Loser	-.008	.005
	(.009)	(.009)
$[\alpha_{11}]$: Retailer Near HS 1st Bin	-.028	-.027
	(.020)	(.020)
$[\alpha_{12}]$: Retailer Near HS 2nd Bin	-.045	-.044
	(.017)***	(.017)***
$[\alpha_{21}]$: Retailer Near ES 1st Bin	-.037	-.036
	(.018)**	(.018)**
$[\alpha_{22}]$: Retailer Near ES 2nd Bin	-.047	-.046
	(.017)***	(.017)***
N	22816	22816
R^2	.567	.567

Column 1 defines 'Home Near Retailer Loser' and 'Home Near Retailer Winner' equal to 1 if the property is within 1900 ft (0.58 km) of retailer applicant losers and winners, respectively. Column 2 defines 'Home Near Retailer Loser' and 'Home Near Retailer Winner' equal to 1 if the property is within 2300 ft (0.70 km) of retailer applicant losers and winners, respectively. Robust standard errors are in parentheses.

Fixed effects: month-year, census tract, zipcode, zoning.

X_{ij}: property characteristics, precinct-level i-502 referendum results, elementary school quality, near lottery loser address for schools.
$***$: significant at 1% level. $**$: significant at 5% level.

Table 1.9: Effect of Retailer Entry on Property Values - 2 bins each

log(Price)	
[γ_{11}]: Home Near Retailer Winner 1st Bin	-.053
	(.013)***
[γ_{12}]: Home Near Retailer Winner 2nd Bin	-.017
	(.012)
[γ_2]: Home Near Retailer Loser	.004
	(.009)
[α_{11}]: Retailer Near HS 1st Bin	-.025
	(.021)
[α_{12}]: Retailer Near HS 2nd Bin	-.043
	(.017)**
[α_{21}]: Retailer Near ES 1st Bin	-.046
	(.019)**
[α_{22}]:Retailer Near ES 2nd Bin	-.048
	(.017)***
Retailer Near ES Loser	-.015
	(.014)
Retailer Near HS Loser	.009
	(.021)
N	22816
R^2	.567

Column 1 defines 'Home Near Retailer Loser' and 'Home Near Retailer Winner' equal to 1 if the property is within 1900 ft (0.58 km) of retailer applicant losers and winners, respectively. Column 2 defines 'Home Near Retailer Loser' and 'Home Near Retailer Winner' equal to 1 if the property is within 2300 ft (0.70 km) of retailer applicant losers and winners, respectively. Robust standard errors are in parentheses.

Fixed effects: month-year, census tract, zipcode, zoning.

X_{ij}: property characteristics, precinct-level i-502 referendum results, elementary school quality, near lottery loser address for schools.
$***$: significant at 1% level. $**$: significant at 5% level.

1.5.2.1 Interpreting Hedonic Coefficients

A drop in property values of 2.5% when a retailer opens near a property is economically significant. The average home in King County, WA during the data's time period is \$579,857, so a drop of 2.5% would be equivalent to \$14,496 that is lost compared to similar properties that did not have a retailer locate nearby. A drop in property values of 4.5% when a retailer opens near a property's assigned school is also economically significant, of about \$26,093. While these losses arguably can be offset by rapid appreciation as witnessed in the Seattle metro area in the last decade, the urban economics literature has extensively documented how certain initial policies in an urban area can lead to more similar measures that reinforce the initial policy's effect [20], either leading to more positive or more negative effects in the long-term. One may worry that the presence of cannabis stores in one neighborhood may lead to more urban disamenities, thus depressing the neighborhood for the medium-to-long-term future.

The reduced-form analyses on retailer price competition and on property prices serve as motivating evidence that the imposed location restrictions affect the cannabis market structure and, without banning the market, are able to mitigate the market's externality on residents. I use these pieces of evidence as building blocks for a structural model that endogenizes firms' decisions of entry and location, using the existing regulations as constraints on firms' choices.

1.6 Model

I develop a structural model of consumer demand and firm entry and location to study the welfare impact of location restrictions around sensitive-use areas for cannabis retailers. I incorporate the license and location restrictions as constraints on firms' decision making.

[20] See Shertzer, Twinam and Walsh (2018).

For computational feasibility reasons, I divide the larger jurisdictions into disjoint location sets, which restrict where in a jurisdiction firms can choose to locate [21]. Firms choose to locate in census tracts l, which compose location sets $\mathcal{A}_{jm}$, which compose jurisdictions m.

$$\text{Census tracts } l \in \mathcal{L} \subseteq \text{Location Sets } \mathcal{A}_{jm} \in \cup_{j=1}^{|M|} \mathcal{A}_{jm} \subseteq \text{Jurisdictions } m \in \mathcal{M}$$

To make the model computationally feasible to estimate, firms in a location set only consider the game they play with the other competitors in that location set, and assume that firms in other location sets locate in the population-weighted location set centroid. Conceptually, this behavioral assumption is analogous to an oblivious equilibrium, where firms in one market know the number of firms in another market but do not keep track of everybody's state variables. This can also help reflect the fact that applicants were local businesspeople and had a preference for certain neighborhoods.

1.6.0.1 Creating Location Sets

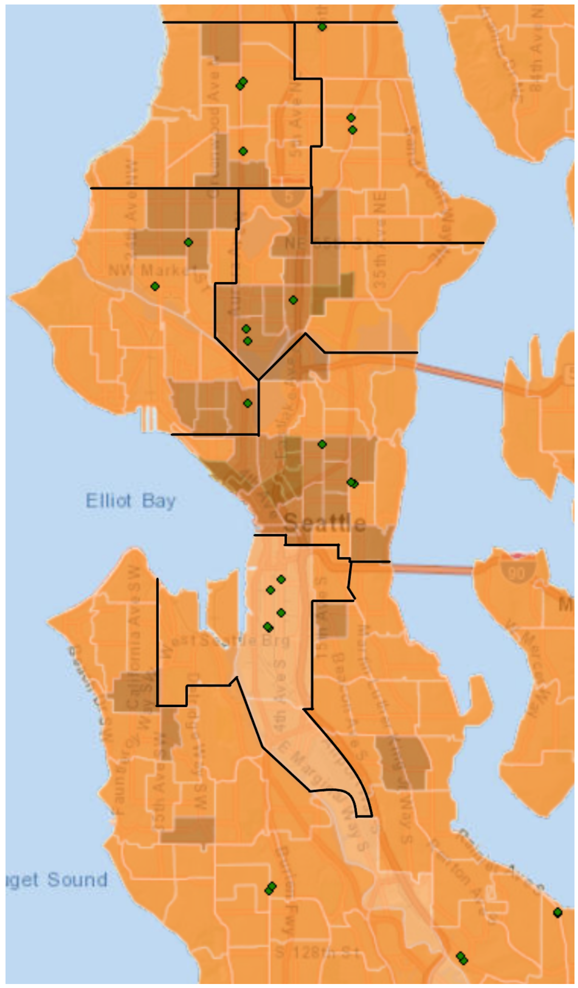
The goal is to create as few location sets as possible [22] while maintaining the estimation computationally feasible. The criterion used is as follows: if a jurisdiction had up to 3 available licenses or up to 20 census tracts, I consider it one location set. Otherwise, I divide the jurisdiction into location sets until the criterion holds. For example, the city of Kirkland, WA in King County had 2 available licenses and 9 census tracts, so it is small enough to count as one location set. On the other hand, the city of Bellevue had 4 available licenses and 29 census tracts so it is split into two location sets. Figure 6 shows Seattle, the

[21] The full-blown model (allowing full demand spillovers, jurisdictions as entire location sets) can be computationally infeasible to estimate if we have more than, for example, 3 firms and 20 locations in a jurisdiction. A quick calculation shows that the total number of computations required, per parameter candidate, in the location decision game when the order is revealed for n firms and l locations is l^n. $20^3 = 8000$, but $20^4 = 160,000$. Seattle's full case would require 131^{21} computations for each parameter candidate in stage 2 and 21! orders in stage 1, both of which are computationally infeasible.

[22] Being conservative with the number of location sets allows us to more naturally use the market's jurisdiction-level license regulations without additional assumptions on firm behavior.

largest jurisdiction with 131 census tracts and 21 licenses, split into 6 location sets [23]. There are a total of 122 location sets, having a minimum of 1 firm to a maximum of 4 firms each.

Figure 1.6: Seattle Divided into 6 Location Sets



A natural question that arises is, once the criterion declares that a certain jurisdiction should be split into location sets, how to carve up the location sets. Often, cities designate subdivisions and neighborhoods based a combination of geographical and demographic factors, so I follow some of these existing subdivisions when dividing jurisidictions into location sets. Anecdotally, a retailer in a trendy, bohemian neighborhood of a city recalled his neigh-

[23]The Appendix shows how Seattle is split into 6 location sets, as well as the full list of location sets.

borhood choice based on being in tune with the neighbors' cannabis-related preferences. A different retailer, on the other hand, explained his desire to be near a college campus to serve that demographic on the basis of different preferences both in price and quality. Geographically, these subdivisions usually follow natural boundaries like rivers or lakes, or large artificial boundaries like interstate highways [24].

The setting for the model includes potential firms $f \in \mathcal{F}_m$, $|\mathcal{A}_m| = \sum_j |\mathcal{A}_{jm}|$ locations in each jurisdiction m, and the order of the location decision game, revealed in stage 2. In stage 1, firms' expectation is that this order is realized according to a uniform distribution. Firms receive a normally distributed shock ϵ_{LS} at the beginning of stage 1 and a logit shock $\epsilon_f(a)$ at the beginning of stage 2. They are ex ante identical in stage 1 at the location-set level. A timeline of the game's decisions is given below:

1.6.0.2 Stages of the Game

Stage 1 (Application): Potential firms simultaneously decide to submit an application in a jurisdiction where the regulator has a cap of $\bar{n}$ firms. Potential firms in a location set $\mathcal{A}_{jm}$ all receive the same normally distributed shock.

Regulator gives out licenses. In those jurisdictions where the cap binds, licenses are awarded via a lottery. Order of moves is 'revealed' in each location set/jurisdiction.

Stage 2 (Location): Licensed firms sequentially decide where to enter. Firms receive a publicly known firm-location-specific logit shock.

Stage 3 (Price-Setting): Firms play a Nash-Bertrand pricing game.

Stage 4 (Consumer Demand): Consumer purchase products at a nearby retailer.

Since the first stages take expectations of later stages and thus require the latter stage

[24] An alternative method would involve selecting location sets that achieves the desired computational feasibility through a k-nearest neighbors method that takes user discretion out of the location set selection.

parameters, I describe the model in reverse order, starting from consumer demand.

1.6.1 Consumer Demand

Market size is defined as in Hollenbeck and Uetake (2019): potential consumption of cannabis in Washington State:

$$M_z = [Population > 21] \times 4 \tag{1.4}$$

Where z is a census tract. Potential consumption is set at 4 times the population over 21 years old to allow for up to 4 grams or units per person per month. I assume consumers live at the population-weighted center of census tracts z. Each census tract is characterized through d_z, the distance between census tract z's population center and each retailer's coordinates D_z, demographic information on census tract z. Consumers h at location z choose a firm f from $\mathcal{F}_h$, the set of firms in their choice set, and select product j from f's product set, $\mathcal{J}_f$. Products are aggregated at the product category level, so each retailer has at most 4 products (usables, solid edibles, liquid edibles, inhalables).

A consumer's choice set is $\mathcal{B}_{h(z)} = \{(j, f) | f \in \mathcal{F}_h, d_{fh(z)} \leq r_h\}$ as in Holmes (2011) and Thomas (2019), where $\mathcal{F}_h$ is the set of firms available to household h at z. Choice sets are exogenous, and chosen so that all consumers have at least 3 firms.

I specify a nested-logit demand model that includes distance between the consumer's location and the firm's location. Consumption of (j, f) yields utility

$$u_{h(z)jft} = \alpha(1 + \tau_m)p_{jft} + x_{jft}\beta + \xi_{jft} + d(z_h, z_f, D_z; \lambda) + \bar{\epsilon}_{hjft} \tag{1.5}$$

where d is disutility generated by transportation costs

$$d_{hf} = d(z_h, z_f, D_z; \lambda) = \lambda_1 dr(z_h, z_f) + \lambda_2 dr(z_h, z_f) \times ln(PopDen(z_h)) \tag{1.6}$$

$\bar{\epsilon}_{hjft} = \zeta_{hf} + (1 - \rho)\epsilon_{hjft}$ is an i.i.d. Type I Extreme Value taste shock, composed of ζ_{hf}, the idiosyncratic firm shock and ϵ_{hjft}, the product-level shock, p_{jft} is the pre-tax retail price, before taxes, of good j at firm f, τ_m is the jurisdiction's total sales tax, x_{jft} are product characteristics such as a constant and chemical potency, number of categories offered, and number of brands offered, $dr(z_h, z_f)$ is the distance between consumer at h and firm f, and $PopDen(z_h)$ is the population density at location z_h. [25].

The outside option is

$$u_{h0} = \Pi D_h + \gamma_{h0} + \epsilon_{h0} \tag{1.9}$$

where D_z is a vector of demographic characteristics (percentage of people above age 45, logged population density, logged median income) and γ_{h0} is normalized to 0. The outside option represents any cannabis purchased outside the legal recreational market.

The choice probability of consumer h in census tract z of purchasing product j from firm f is:

$$s_{zjft}(\delta_{jft}, \theta, D_z) = \frac{exp(\delta_{jft} + d_{zf}))/(1-\rho)}{exp(I_{zf})/(1-\rho)} \frac{I_{zf}}{I_z} \tag{1.10}$$

Where the inclusive value term is defined as:

$$I_{zf} = (1-\rho) log \sum_{j \in F} exp((\delta_{fjt} + d_{zf})/(1-\rho)) \tag{1.11}$$

and

$$I_z = ln(1 + \sum_f exp(I_{zf})) \tag{1.12}$$

[25] Note that this set up is a special case of the random coefficients nested-logit (RCNL) model, where the mean product utility is

$$\delta_{jft} = \alpha(1+\tau_m)p_{jft} + \beta X_{jft} + \xi_{jft} \tag{1.7}$$

and the household-specific utility is

$$d_{fh(z)} = X_2 \times [\Pi d_h + \Sigma \nu_h] = \Pi d_h \tag{1.8}$$

and we set $\Sigma = 0$, $X_2 = 1$, and $d_h = (dr(z_h, z_f), dr(z_h, z_f) * log(PopDen_{z_h})$

Then, total demand at census tract z for product j by firm f is $s_{zjft} \times M_z$, where M_z is the number of people in the census tract z times 4 (to allow for up to 4 grams or units per person per month). Thus, the total demand for product j in firm f in month t is

$$Q_{jft} = \sum_{z \in \mathcal{Z}_f} s_{zjft} \times M_z \tag{1.13}$$

where $\mathcal{Z}_f = \{z | f \in \mathcal{B}_z\}$ is the set of census tracts that have firm f in their choice sets.

1.6.2 Retailer Price-Setting

Retailers set prices each month that they are in the market. I assume each store is an independent retailer [26]. Firms maximize their own variable profits:

$$r_f = \sum_{j \in \mathcal{J}_f} (p_{jf} - c_{jf}) \times Q_{jf} \tag{1.14}$$

where $c_{jf} = \bar{c}_{jf} + \omega_{jf}$, the cost of product j, is the wholesale cost observed in the data plus an unobserved marginal cost. Observed and unobserved marginal costs are assumed to have independent distributions, F_c and F_ω, respectively, i.i.d. across products.

Taking first-order conditions with respect to a product's price, we obtain:

$$\frac{\partial r_f}{\partial p_{jft}} = Q_{jft} + \sum_{j' \in \mathcal{J}_f} (p_{j'ft} - c_{j'ft}) \times \frac{\partial Q_{j'ft}}{\partial p_{jft}} = 0 \tag{1.15}$$

The firms' first-order conditions follow the matrix form:

$$\mathbf{p}_f - \mathbf{c}_f + \Delta^{-1} \mathbf{Q}_f = 0 \tag{1.16}$$

[26] The market initially allowed for up to 3 licenses per applicant, allowing the possibility of chains. While some retailers operate as chains, the market's early stages do not appear to show chain-driven advantages. Anecdotally, some of the chain-affiliated retailers appeared to make pricing and inventory purchasing decisions at the establishment level, independent of the headquarters, while using the chain image to provide a more standardized customer experience, e.g. budtender training, rewards programs, etc.

where Δ is a matrix of cross-price derivatives, $\frac{\partial Q_{j'ft}}{\partial p_{jft}}$.

The first-order conditions are used to obtain counterfactual prices when I vary the distances between consumers and firms in the location decision stage.

1.6.3 Location Decision

The location decision stage occurs at the beginning of the market, after firms obtain their licenses.

Players: Firms $f = 1, \ldots, N$ that obtained a license in jurisdiction m. Each firm is endowed with a location set $\mathcal{A}_{jm}$ at the beginning of the game. There are $|\mathcal{M}|$ jurisdictions.

Actions: At the beginning of the market, each firm f chooses a location $a_f \in \mathcal{A}_{jm}$, where $\mathcal{A}_{jm} = \{1, \ldots, L_{jm}\}$ is a firm f's choice set in its location set. In this setting, an action is a census tract l in the jurisdiction m. Firms only choose a location within their assigned location set.

Firms choose locations based on the sum of present discounted profits they expect to receive over their time present in the market. Firms receive a $\epsilon_f(a)$, an unobservable (to the econometrician) firm-action-specific shock, which helps rationalize differences in location choices beyond demand and costs [27].

Information Set $\mathcal{I}_2$: licensed firms know the information set of the entry stage $\mathcal{I}_1$, the identity of firms that received a license, the order of the sequential game, and each other's $\epsilon_f(a)$. At this point, firms know everything, making this is a game of complete information.

I assume that the order for each location set is realized at the beginning of the location decision stage and assume firms know the order.

[27] In practice, the shock helps rationalize the fact that retailers did not have access to financial services, which precluded them from getting access to retail space that was being paid through a mortgage and would otherwise have been profitable and available. This real-life complication further restricts the locations that retailers could choose to open their businesses.

Payoffs: The profit function each firm faces at the beginning of the market is

$$\pi_f(a, x, \epsilon) = max(\bar{\pi}_f(a, x) + \epsilon_f(a), 0) \tag{1.17}$$

where

$$\bar{\pi}_f(a, x) = r_f(a, x) - s(a_f, x) \tag{1.18}$$

where $r_f(a, x)$ are variable profits of firm f choosing location l and its competitors choosing locations l', $s(a_f, x)$ is a parametric function that represents location-specific fixed costs of the action firm f chooses. Not choosing any location yields payoff 0.

Equilibrium: The equilibrium of the location decision game is subgame perfect, where the game is solved by backward induction. The game occurs simultaneously in each location set in a jurisdiction.

Example: Suppose that in jurisdiction m, there are 2 firms and 2 locations, and realized order of moves is firm 1 moves first. Then the game is solved by: firm 1 chooses its optimal location, a_1^*. Then firm 2, observing firm 1's decision, chooses its optimal location, $a_2^*(a_1^*)$. The subgame perfect equilibrium is $(a_1^*, a_2^*(a_1^*))$.

I allow unrestricted demand spillovers for consumers, meaning that consumers can purchase goods at any firm in any location set or jurisdiction given the assigned radius r_h, specified in the demand system's choice set. However, I allow spillovers for firms across location sets and jurisdictions in a very specific way: otherwise, a firm in a location set would have to consider where firms in the adjacent location sets will locate, which can become computationally infeasible. The restrictions on firms limits the neighborhoods in the jurisdiction where they can locate. These assumptions allow me to keep track of demand in other location sets to a certain extent when deciding locations in a given location set. Conceptually, one can think of the behavioral assumptions of firms as an oblivious equilibrium, where firms in a location set know the number of firms in an adjacent location set and have a general idea of what they may do without fully keeping track of each other's state variables.

1.6.4 Application Game

The first stage of the game involves potential firms applying to secure a license to operate in the market. Conceptually, the game is akin to a standard model of entry, but potential firms are not guaranteed to enter when they apply due to the license restrictions.

I nest binding/nonbinding license cap outcomes in a standard entry model, such that a license cap binding or not binding is an outcome of the game. Note that if the cap goes to infinity, the model collapses to the Bresnahan and Reiss (1991) entry model. On top of this, I augment this model to include location sets. Adding location sets constitute a nontrivial wrinkle since the firms' decisions to apply depends on 1) profitability at the location set level that interacts across location sets and across jurisdictions and 2) binding/nonbinding outcome at the jurisdiction level.

Players: N_m identical potential firms $f \in \mathcal{F}_m$ in jurisdictions $m \in \mathcal{M}$.

If a jurisdiction is large enough, potential firms $f \in \mathcal{F}_m$ are assigned a location set $\mathcal{A}_{jm} \subseteq \mathcal{A}_m$ according to a probability distribution, which can be either uniform or dependent on the population/demand/other characteristics of the market. The location set that potential firms are assigned to is known to all other potential firms.

The number of potential firms by jurisdiction varies based on population: e.g I fix the number of potential firms for Seattle city limits, and scale up or down in other jurisdictions based on the population difference [28].

Actions: Simultaneously, firms apply or do not apply for a license in their jurisdiction m.

Information set: $\mathcal{I}_1$. Potential firms know each potential firm's location set $\mathcal{A}_{jm}$, demand and costs at each action $a_f \in \mathcal{A}_{jm}$, and the number of available licenses $\bar{n}_m$ in the

[28]For example, if Seattle has 300 potential firms and Tacoma has half of Seattle's population, then Tacoma would have 150 potential firms

jurisdiction. Potential firms have an expectation that the order of moves in which firms choose locations in stage 2 will be revealed in stage 2 according to a uniform distribution.

Payoffs: Potential firms face an expected profit function and decide to apply based on a zero-profit condition.

The expected profit equation is very similar to a simplified case without location sets. The total number of applicants n_m in a jurisdiction m is equal to the sum of applicants across the location sets that compose a jurisdiction m.

$$\begin{aligned} E[\pi_{f,LS}(a,x)|\mathfrak{I}] = \\ & 1_{\{\sum_{LS} n_{LS} > \bar{n}_m\}} \left[\frac{\bar{n}_m}{\sum_{LS} n_{LS}} \left[E[r_{LS}(\cdot) - s_{LS}(\cdot)|\mathfrak{I}] \right] \right] \\ & + 1_{\{\sum_{LS} n_{LS} \leq \bar{n}_m\}} \left[E[r_{LS}(\cdot) - s_{LS}(\cdot)|\mathfrak{I}] \right] - F_{LS} \end{aligned} \tag{1.19}$$

where $1_{\{\sum_{LS} n_{LS} \geq \bar{n}_m\}}$ is an indicator of whether the total number of applicants in a jurisdiction exceeds the number of licenses, thus implying a binding cap, $\frac{\bar{n}_m}{\sum_{LS} n_{LS}}$ is the probability that an applicant in a binding jurisdiction receives a license, the inner expectation is over possible orders in stage 2 and how many competitors they expect to have ($[k_j]$), $r_{LS}(\cdot)$ are variable profits, calculated from demand and marginal costs, $s_{LS}(\cdot)$ are location-specific fixed costs, calculated from cost of real estate at the chosen location, estimated in the location game, and F_{LS} is the sunk cost of applying/entering.

Note that every potential firm pays a sunk cost, even those in binding jurisdictions that may not receive a license. Also, any profits potential firms expect to make once they receive a license (revenues minus marginal costs minus cost of real estate) is weighted by the probability of getting a license.

1.6.4.1 Modeling Expectations

Potential firms know that once they get a license, they will play a sequential game of location decision. At the time of applying, however, they don't know the order of moves.

Thus, they have expectations over the profits they can obtain from applying based on the available locations.

Expectations over distributions

Since the $\epsilon_f(LS, a)$ is revealed to firms in stage 2, I integrate firms' expected profits upon receiving a license by the distribution of the firm-location specific shock they will receive in stage 2. In addition, I also integrate over the distribution of orderings, from where the order revealed in stage 2 will be drawn from.

Example of taking expectations over orderings:

I provide a brief example of how expectations over orderings are computed:

Suppose we have 2 firms in one location set with two locations, $\mathcal{A}_m = \{a_1, a_2\}$. Suppose firms anticipate that the order in stage 2 is follows a uniform distribution so there are $n_m! = 2! = 2$ possible orders):

Assume that choosing location 1 is more profitable than choosing location 2 and that if a firm chooses location 1 first, then the second-mover chooses location 2. The profits for firm 1 equal the probability of firm 1 moving first (which equals 0.5) times the payoff of selecting the optimal location if firm 1 moves first (in this toy example, it is location 1 (and firm 2 selecting location 2)), plus the probability of firm 1 moving second (which equals 0.5) times the payoff of selecting the second-best location (in this toy example, location 2 (and firm 2 selecting location 1)). Then, the expected profits of firm 1 are:

$$\begin{aligned} E[r_1(a,x) - s_1(a,x)|\mathfrak{I}] = Prob(f_1^1)(r_1(a_1^1, x) - s_1(a_1^1, x)) \\ + Prob(f_1^2)(r_1(a_1^2, x) - s_1(a_1^2, x)) \end{aligned} \tag{1.20}$$

with the locations in each clause chosen by the aforementioned logit-style choice probabilities.

If there are, for example, 3 firms applying, there will be $3! = 6$ orders, and so on.

Case 1: Jurisdictions with more than one location set, if the cap is non-binding:

Each location set has potential firms applying until it is not profitable to apply in that location set. Effectively, there is a zero-profit condition at the location-set level. For example, let $\bar{n}_m = 4$, $n_{\mathcal{A}_1} = 2$ and $n_{\mathcal{A}_2} = 2$. This means that 2 potential firms applied in location set $\mathcal{A}_1$, which implies a 3rd applicant would not find it profitable, and likewise for location set $\mathcal{A}_2$. Since the cap does not bind, there is a zero-profit condition in effect for each location set.

Case 2: Jurisdictions with more than one location set, if the cap is binding:

I describe three main features that appear when the cap is binding for large jurisdictions: first, the profit function exhibits a kink. Second, I describe how to compute the expected number of firms that will get a license in each location set through the lottery. Third, the interaction between n_{LS}'s within a jurisdiction.

First, I explain how the expected profit function changes as we move from $\bar{n}_m$ (no lottery conducted) applicants to $\bar{n}_m + 1$ (lottery is conducted) applicants. There will be a kink in the profit function as a function of number of applicants at the jurisdiction level. Before the cap, the profit function would decrease at some fixed slope. Once it exceeds the cap, the profit function will still decrease in the number of applicants but at a different slope. In practice, this jump is minimized by weighing potential firms' expected profits by the probability of obtaining a license.

Second, suppose we already have the number of applicants $\{n^*_{\mathcal{A}_{jm}}\}_j$ for an equilibrium. Since the number of licenses in each location set will be awarded by lottery, we can compute the expected number of licenses for each location set. Call this statistic $[k_{\mathcal{A}_j}]$. I can calculate $[k_j]$ by multiplying the likelihood of getting a license, $\frac{\bar{n}_m}{\sum_{LS} n_{LS}}$, by the number of applicants $n_{\mathcal{A}_j}$ in location set $\mathcal{A}_j$ in jurisdiction m and obtaining the whole number from the expression.

Example:

I show how $[k_j]$ is computed using a simplified version of the description above. Let:

- $\bar{n}_m = 4$: number of licenses for a jurisdiction m.
- $N_m = 10$: number of potential firms in jurisdiction m.
- $j = 2$: number of location sets $\mathcal{A}_{jm}$ in jurisdiction m.
- $n_{\mathcal{A}_1} = 5$: number of potential firms assigned to location set $\mathcal{A}_1$.
- $n_{\mathcal{A}_2} = 5$: number of potential firms assigned to location set $\mathcal{A}_2$.
- $n^*_{\mathcal{A}_1} = 3$: number of potential firms that apply in location set $\mathcal{A}_1$.
- $n^*_{\mathcal{A}_2} = 2$: number of potential firms that apply in location set $\mathcal{A}_2$.
- $n_m = \sum_j n^*_{\mathcal{A}_j} = 5$: number of potential firms that apply in jurisdiction m.

$[k_{\mathcal{A}_1}] = [\frac{4}{3+2}3] = [2.4] = 2$

$[k_{\mathcal{A}_2}] = [\frac{4}{3+2}2] = [1.6] = 2$

In this example, we can expect 2 firms to receive licenses in location set $\mathcal{A}_1$ and 2 firms to receive licenses in location set $\mathcal{A}_2$. Note that $\sum_{LS}[k_{LS}] = \bar{n}_m$. [29].

Once we have the $[k_{\mathcal{A}_j}]$, we can calculate the expected profits upon getting a license, $E[r_f(\cdot) - s_f(\cdot)|\mathfrak{I}]$ by taking expectations over orderings based on the number of competitors a firm is expected to have, just as described in the nonbinding case section.

Thirdly, the number of applicants in location sets within a jurisdiction may interact, making it unclear how an equilibrium is computed. For example, it may occur that 3 potential

[29] This equality holds for most simple examples but is not a mathematical result due to rounding: in those jurisdictions where equality is not satisfied, I order location sets in the jurisdiction by population and obtain equality by assigning fewer applicants to the less populated location sets.

firms applying in location set 1 may prompt only 2 potential firms to apply in location set 2, but if it location set 2 had moved first, more potential firms could have applied. I solve this issue by imposing timing assumptions across location sets [30].

Equilibrium: As in Bresnahan and Reiss (1991), the equilibrium is in the number of firms, meaning that the identity of applicants is unimportant. The equilibrium number of applicant firms in each market m is defined as $\{N_m\}_{m=1}^{\mathcal{M}}$. It is governed by a zero-profit condition at the location-set level such that

$$E[\pi_f(N_{LS}^*)|\mathcal{I}] \geq 0 > E[\pi_f(N_{LS}^* + 1)|\mathcal{I}] \tag{1.21}$$

In jurisdictions with more than one location set, $n_m = \sum_{LS} n_{LS}$, where the number of applicants in a location set is such that no applicant is willing to deviate. This means that the equilibrium vector for a jurisdiction, if the jurisdiction has more than 1 location set, will be an j-vector of number of applicants n_{LS_j}, one for each location set. If a jurisdiction only has one location set, it has a scalar number of firms applying in equilibrium, which is exactly the Bresnahan and Reiss (1991) model.

Without additional assumptions, the equilibrium in number of applicants n_m is not unique. First, there may be multiple equilibria in a jurisdiction where N_m^* firms apply in jurisdiction m but depending on which location set 'moves' first, leading to different combinations of N_{LS}^*. I resolve this multiple equilibria issue in N's in location sets by introducing a timing assumption in the order of moves: I assume the most populated location set in a jurisdiction move first. Second, there may be multiple equilibria in N's across jurisdictions because jurisdictions are related through the spillovers in the consumer demand stage. I resolve this multiple equilibria issue in jurisdictions by assuming the most populated

[30] I address the third point in more detail in the equilibrium walk-through section in the Appendix.

jurisdictions 'move' first. These two conditions ensure a unique equilibrium in the number of applicants.

I now turn to a description of estimable versions of the game described above, as well as the methods used to estimate the structural parameters.

1.7 Estimation Description

Because the earlier stages use structural parameters that are recovered in the later stages, I describe the estimation steps by starting from the last stage and proceeding in a backward fashion.

1.7.1 Demand Estimation

I estimate the consumer demand model following Berry, Levinsohn, and Pakes (1995). I follow Grigolon and Verboven (2014)'s method of modifying the Berry, Levinsohn and Pakes (1995) contraction mapping for a nested-logit model to obtain the unique vector $\delta^*_{jf}(x_{jf}, s_{jf}; \theta)$, which obtains mean utility values from observed market shares s^{obs}_{jf}: equating the observed market share vector to the predicted market share vector $s^{obs}_{jf} = s_{jf}(\delta_{jf}; \theta)$. However, since the consumer demand model does not have clearly defined markets [31], I am unable to compute market shares in the traditional way. Instead, I use observed and model quantities at the product-firm-month level:

$$\delta^{t+1}_{jf} = \delta^t_{jf} + (1 - \rho)(ln(Q^{obs}_{jf}) - ln(Q_{jf}(\delta^t_{jf}))) \tag{1.22}$$

I concentrate out the linear parameters and estimate the model by searching over the nonlinear parameters [32] such that the objective function of the GMM is minimized [33]. For

[31] The choice set constructed for each consumer allows consumers to travel across jurisdictions, so there is no traditional notion of a clearly defined 'market' in this application.

[32] Using the *fminsearch* command in MATLAB, which uses the Nelder-Mead method

[33] I also estimate this model via the MPEC method outlined in Dubé, Fox and Su (2012), yielding similar estimates.

starting values, I use $W = (Z'Z)^{-1}$ for the GMM weighting matrix and the coefficients from a 2SLS regression.

1.7.1.1 Instruments

The model suffers from the usual endogeneity problem in demand estimation: after we take the variation from product categories, store and trimester-year fixed effects, there is an unobservable ξ_{jft} that varies over time and within retailers. We may be concerned about a demand shock to a product category at a retailer in a given month. To address this potential endogeneity concern, I include a number of instruments.

I include the usual BLP instruments, which are the average characteristics of a firm's other products, and the average characteristics of competitor's products. I also include the wholesale price of competitors' products. A potentially important measure of product quality is, beyond the potency variables in the demand system, the amount of THCA, a non-psychoactive cannabinoid that is a precursor to THC. As the product dries, THCA converts into THC and depending on the mode of consumption (e.g. combustion), the user may obtain more THC out of the product. More THCA present may impact price due to the product being harvested more recently, something I do not observe. Lastly, I include the logged distance to the nearest competitor, which, as shown in the reduced-form results, is an important variable for price competition among retailers.

I also include instruments that help identify the nonlinear components of preferences Σ, Π, and ρ. Identification requires the conditional shares of the inside goods, which are represented by the percentage of product category j sold at store f, to have exogenous variation. I include the monthly number of products in a product category sold by a retailer, the mean sales price of within-retailer competing products, and the mean values of the cost shifters for within-retailer competing products.

The demand estimation yields the parameters governing consumers' preferences toward price, product characteristics, travel costs, and substitution within and across stores. These parameters are used in the retail price-setting stage, described below.

1.7.2 Retail Price-Setting

Following Thomas (2019) and Wollmann (2018), I use the pricing equation and the demand coefficients to obtain the unobserved marginal costs and, when recomputing the equilibrium in the counterfactual section, to compute new equilibrium prices. Inserting the demand estimates into the pricing equation yields an implicit function of p_{jft}, which can be backed out via iterated best response.

$$p_f = c_f + \Delta^{-1}(\theta)Q_f(\theta, p_f) \tag{1.23}$$

I follow Morrow and Skerlos (2010)'s method of modifying the first-order condition to construct a fixed point mapping of the price [34].

The unobserved marginal costs ω_{jft} are obtained via the following inversion of the first-order condition:

$$\omega_f = p_f - \bar{c}_f - \Delta^{-1}Q_f(p_f) \tag{1.24}$$

When computing variable profits for each possible alternative location arrangement, firms consider different locations for their store, which changes their distance to consumers, which affects the quantities sold. Firms respond to this mechanism by adjusting their prices according to the first-order condition above.

[34] I also obtain the new equilibrium prices by following Miravete, Seim and Thurk (2018)'s approach, yielding similar results.

1.7.3 Location Decision

Each firm chooses the location in their assigned location set that yields the greatest lifetime profits, in the jurisdiction they received a license, based on competitors' optimal decisions. Firms only search over their assigned location set or jurisdiction. In this stage, the order is revealed to firms. The game is now complete information.

The game is sequential, meaning that players move in the order given to them by 'nature'. I assume the observed vector of locations is the subgame perfect equilibrium of this game and the observed order in the data is the realized order. Before specifying the estimation of the location-specific fixed costs, I parameterize the game's payoffs and actions to make the model estimable:

1.7.3.1 Parameterization

Firms choose the location (a census tract) that yields the greatest present discounted value of profits $\pi_f(a, x, \epsilon)$, given its competitors' decisions and the realized order of moves. Recall that firms' profits are of the form:

$$\pi_f(a, x, \epsilon) = max(\bar{\pi}_f + \epsilon_f(a), 0) \tag{1.25}$$

where $\bar{\pi}_f$ are the sum of present discounted payoffs for a firm f over its lifetime from choosing an action a. If a firm does not choose any location, it receives a payoff of 0. The profits $\bar{\pi}_f$ from choosing a location take the form:

$$\bar{\pi}_f(a, x, \epsilon) = \sum_{t=1}^{138} \beta^t [r_{ft}(a, x) - s_{ft}(a, x)] + \epsilon_f(a) \tag{1.26}$$

where the monthly cost of location is kept fixed over time, $s_{ft}(a, x) = s_f(a, x)$, the variable profits are time-varying according to variables $(p_{jft}, x_{jft}, \xi_{jft})$ and the monthly fixed effects, and the discount factor β is set at 0.98. Since I only observe these variables up until the end of the data, I draw 120 additional months worth of data from the last 3 months of available data to construct the monthly variable profits for future time periods [35].

I further parameterize the terms inside the profit function to obtain:

$$r_f(a,x) = r_f(a_f, a_{-f}; x, \theta) \tag{1.27}$$

which are the variable profits of firm f choosing action a_f and its competitors choosing a_{-f}. Further parameterization of the variable profit to include the demand parameters yields:

$$r_{ft}(a_f, a_{-f}; x, \theta) = \sum_{j \in \mathcal{J}_{ft}} (p_{jft}(x) - c_{jft}(x)) Q_{jft}(a_f, a_{-f}; x, \theta) \tag{1.28}$$

where $\mathcal{J}_{ft}$ is the set of products that firm f offers in month t, Q_{jft} is the quantity sold (which depends on its competitors), at sales price p_{jft} and at wholesale price c_{jft},

$$s_{ft}(a_f, x) = s(a_f, x; \gamma) = \gamma X(a_f) \tag{1.29}$$

which is the location-specific fixed cost of firm f choosing action a_f, which reflects the cost of real estate X in location l in jurisdiction m.

I use average monthly rent and mortgage payments as proxies for the cost of real estate in census tract l.

$\epsilon_f(a)$ is a firm-location-specific Type I Extreme Value unobservable (to the econometrician).

1.7.3.2 Equilibrium computation

To find the equilibrium, I assume firms move sequentially and the order is announced at the beginning of this stage, according to a uniform distribution [36]. To estimate γ, the

[35] I assume firms exist for 10 years after the data ends. 10 years, equivalent to 120 months, plus the 18 months of the data, equals 138 months of operation.

[36] Meaning all possible orderings are equally likely.

parameters governing the location-specific fixed costs, I use a method of simulated moments estimator to find the γ that minimizes the deviations of the predicted equilibrium of location decisions from the observed location decisions [37].

The reason for taking a sequential route is twofold. First, to more accurately reflect the idea that once a firm opens in a given location, other firms may react to this and choose a potentially different location [38]. Second, a sequential model can reduce the time required to compute the equilibrium. Using an iterated best response method to solve a simultaneous-move location decision game, the procedure would loop back when it reaches the n^{th} firm so that the first firm can re-optimize, and given my number of locations, the equilibrium computation can quickly become computationally burdensome.

This procedure involves using the order of moves observed in the data to construct moments which include the equilibrium location decisions, and matching the model's location decisions with the data's location decisions. I explain how to construct the moments for the method of simulated moments estimator.

1.7.3.3 Method of simulated moments estimator

Recall that a market m is a location set or a jurisdiction (if a jurisdiction is its own location set). Let z_m be exogenous data for market m: I use the precint-level I-502 referendum results 'yes' percentages and the number of underage people in each census tract, as well as demographic variables that were excluded from the demand estimation. I provide a brief walkthrough of how the moments are constructed:

- First, use the order o_m observed in the data $\mathcal{O}$ for each market m.

[37] Alternatively, I also explain how to estimate the parameters with a maximum simulated likelihood estimator.

[38] This assumption of the game indeed occurs in the data, with about 25% of licensed firms locating farther than a third of a mile from their proposed location.

- Draw ϵ_{sm}, s=1,...,S for each market m. ϵ_{sm} is a vector of shocks, one for each firm-location.

- For the observed order o_m and for each ϵ_{sm}, compute the subgame perfect equilibrium vector of locations $\hat{y}_{sm}(\epsilon_{sm}, o_m, \gamma, z_m)$ for each market using the game tree induced by the realized order and available locations.

- Construct the function $\mu(\cdot)$, which tracks location decisions for each firm in market m.

- The estimator is obtained by subtracting the μ evaluated at the the simulated data from the μ evaluated at the true data as in Ackerberg and Gowrisankaran (2006), taking the form:

$$\begin{aligned} \gamma_{MSM} &= argmin_\gamma G^{MSM} \\ &= argmin_\gamma \| \frac{1}{|LS|} \sum_{m=1}^{|LS|} \sum_{l=1}^{L_m^{N_m}} [\mu(y_m = l) - \frac{1}{S} \sum_s \mu(\hat{y}_{sm}(\epsilon_{sm}, o_m, \gamma, z_m) = l)] \otimes g(z_m) \| \end{aligned} \tag{1.30}$$

For arbitrary functions μ and g. γ is found via a nonlinear search.

I currently specify μ as a function that returns the number 1 if all firms in a certain location set choose the vector of locations l out of all possible permutations of locations $L_m^{N_m}$ and 0 otherwise. As an example, suppose there are 2 firms and 3 locations. Then there are a total of $3^2 = 9$ possible outcomes. Then one location vector could be (l_1, l_3) and the function μ checks whether firms 1 and 2 chose those locations.

The last thing to do is to specify the norm. For a positive definite matrix A [39], the MSM estimator is:

$$\hat{\gamma} = argmin_\gamma G(\gamma)' A G(\gamma) \tag{1.31}$$

[39] Using Continuously Updating Estimator and $A = I$ as the initial weighting matrix.

Thus, γ is a dimension n_γ by 1 parameter, $g(z_m)$ is a $n_\gamma * n_G$ vector for each location set/jurisdiction, $G^{MSM}(\gamma)$ is a $n * n_G$ vector, and A is a $n_G * n_G$ matrix, where n_G is the number of moments, and there are at least n_G instruments.

1.7.3.4 Identification

γ is identified off differences in the cost of real estate between locations l. Since I do not have data on census-tract level monthly lease costs, I proxy the cost of leasing a store $X(a_f)$ with the monthly gross rent for renters in the census tract from the 2014 American Community Survey. I also include the median value of owner-occupied units, as well as selected monthly costs for renters.

γ is identified up to 'scale', so I normalize the location with the lowest cost of real estate. The η parameters from the sunk costs in the application stage described below identify the 'intercept'. The idea is that no matter the location they choose, the difference between the revenue at that location and the cost of leasing at that location is positive, and the fixed cost estimation picks up the level from the remaining variation. If the difference is negative, then that location is not profitable for firm f and is not chosen. I do not allow licensed firms to not choose a location.

With γ estimated, I turn to the $F(\eta)$ sunk cost estimation.

1.7.4 Entry Estimation

I begin by setting a number for the potential firms in Seattle, and then scale down to other jurisdictions based on population [40]. The goal is to estimate the sunk cost of applying

[40] Recall that I observe n_m, $n_{\mathcal{A}_{jm}}$, $\bar{n}_m$, $r_f(\cdot)$, $s_f(\cdot)$, the observed $k_{\mathcal{A}_j}$, and whether a jurisdiction-level cap binds or not from the data and from the previous estimation steps. What I do not observe is the number of potential firms N_m (before applying) and the sunk cost F. A standard approach is to make sensible assumptions on the number of potential firms and estimate the sunk costs. A different method would be to employ an estimate of the sunk cost and back out the number of potential firms. Since I lack detailed data on firms' sunk costs or how much a retail establishment costs, I follow the former approach.

to be a firm in the market.

Before describing the sunk cost estimation strategy, I explain how I parameterize the sunk costs:

1.7.4.1 Parameterization

Let the location-set-level application sunk cost be defined by

$$F_{LS} = \eta X_{LS}^{C} + \epsilon_{LS} \tag{1.32}$$

where X_m^C are location-set-level variables such as logged population, cost-of-living indices, and logged population density. ϵ_{LS} is a mean zero normally distributed shock at the location set level.

1.7.4.2 Constructing the likelihood function

I follow Bresnahan and Reiss (1991) in creating a log likelihood to estimate η [41].

Recall that the expected profit function is of the form

$$\begin{aligned} E[\pi_{f,LS}(a,x)|\mathcal{I}] = \\ & 1_{\{\sum_{LS} n_{LS} > \bar{n}_m\}} \left[\frac{\bar{n}_m}{\sum_{LS} n_{LS}} \left[E[r_{LS}(\cdot) - s_{LS}(\cdot)|\mathcal{I}] \right] \right] + \\ & 1_{\{\sum_{LS} n_{LS} \leq \bar{n}_m\}} \left[E[r_{LS}(\cdot) - s_{LS}(\cdot)|\mathcal{I}] \right] - F_{LS} \end{aligned} \tag{1.33}$$

The expected profit function indicates that the sunk cost for all potential firms is the same, after conditioning for location-set level covariates), regardless of whether the license cap binds or not. This assumption is more innocuous than it appears to be: first, if the license cap binds, expected profits are weighted by the probability of obtaining a license, which drives expected variable profits down. Second, a substantial part of the variation in sunk

[41] The application stage involves evaluating the likelihood function at each market, and has one data point for each location set/jurisdiction: a total of 122 data points.

costs is absorbed in the location-specific fixed costs from stage 2, so the sunk costs F_m is net of differences in cost of real estate and profitability, and is more related to the sunk cost of opening a store in the jurisdiction, which gets more at the 'level' rather than the 'slope'.

The expression above is equivalent to

$$E[\pi_{f,LS}(a,x)|\mathfrak{I}] = V_{LS}(\cdot) - F_{LS} = (V_{LS}(\cdot) - \eta X_{LS}^C) + \epsilon_{LS} = \pi_{LS}(\cdot) + \epsilon_{LS} \tag{1.34}$$

Since N_{LS}^* potential firms applied in each location set, we can assume it was profitable for N_{LS}^* to apply but not for $N_{LS}^* + 1$ firms. We can then obtain a set of inequalities of the following form:

$$V(N_{LS}^*, x_{LS}) - F_{LS} \geq 0 \tag{1.35}$$

and

$$V(N_{LS}^* + 1, x_{LS}) - F_{LS} < 0 \tag{1.36}$$

Combining, we obtain

$$V(N_{LS}^*, x_{LS}) \geq F_{LS} > V(N_{LS}^* + 1, x_{LS}) \tag{1.37}$$

The inequalities serve as bounds that can specify the probability of observing N^* firms:

$$\begin{aligned} &P(V(N_{LS}^*, x_{LS}) \geq \\ &\qquad F_{LS}|x_{LS}) - P(V(N_{LS}^* + 1, x_{LS}) > F|x_{LS}) \\ &\qquad = \Phi(V(N_{LS}^*, x_{LS}, \eta)|x_{LS}) - \Phi(V(N_{LS}^* + 1, x_{LS}, \eta)|x_{LS}) \end{aligned} \tag{1.38}$$

Where $\Phi(\cdot)$ is the cdf of the standard normal distribution, since ϵ_{LS} is assumed normal.

I then construct a likelihood function for N_{LS}^*, the observed number of applicants in each location set. If I assumed independent and identical sampling assumptions, the likelihood would have an 'ordered' dependent variable form:

$$\mathcal{L}(\eta|\{x_{LS}, N^*_{LS}\}) = \sum_{LS=1}^{|LS|} ln(\Phi(V(N^*_{LS}, x_{LS}, \eta)) - \Phi(V(N^*_{LS}+1, x_{LS}, \eta))) \tag{1.39}$$

However, recall that a crucial assumption in Bresnahan and Reiss (1991) is that firms' unobservable profits must be statistically independent across markets. In this model, I assume observed profits are interrelated across location sets and jurisdictions [42]. To maintain internal consistency, I slightly modify the log likelihood and use a joint likelihood function:

$$\mathcal{L}(\eta|\{x_{LS}, N^*_{LS}\}) = ln(\Phi(V(N_1)^*, ..., V(N^*_{LS}), x, \eta) - \Phi(V(N^*_1+1), ..., V(N^*_{LS}+1), x, \eta)) \tag{1.40}$$

where $\Phi(\cdot)$ is a multi-dimensional normal cdf. Once the likelihood function is specified, it is maximized to obtain the estimated η parameters.

To construct the $V(N^*_{LS}+1, x_{LS}, \eta)$ term, I simulate a $n_{LS}+1$th applicant for the jurisdiction/location set. If the license cap in a jurisdiction is already binding, I merely consider the decreased probability of getting a license and its corresponding decrease in expected profits of an additional applicant. If the license cap is nonbinding, I simulate an additional applicant by drawing from the distributions for observed and unobserved product characteristics and costs that were estimated in the previous stages.

I provide a walkthrough of how I construct the $V(N^*_{LS}+1, x_{LS}, \eta)$ term: for a given jurisdiction, I simulate an additional firm with parameters $(\alpha, \beta, \lambda, \rho)$ as estimated in the demand stage and ξ drawn from the recovered distribution F_ξ for that jurisdiction. Suppose $N^*_{LS} = 3$, so I select the 4 most profitable locations in the jurisdiction/location set and 'place' the 4 firms in each permutation of the 4 locations. Each firm serves census tracts with

[42] Due to the nature of demand, which is spatial.

consumers based on the same radius distance as specified in the consumer demand model. For each of these permutations, I can calculate each consumer's choice probabilities $s_{hjf|f}, s_{hft}$, which allows me to calculate each firm's sold quantities Q_{jft}. I can then calculate variable profits for each permutation of locations, which allows me to compute the new 'equilibrium' vector of location decisions for each ordering (4 firms for 4 locations, and depending on who moves first). Finally, I calculate $V(N^*_{LS}+1, x_m, \eta)$.

1.8 Results

1.8.1 Demand Estimates

Table 10 presents estimates from the demand estimation. Most coefficients have the expected signs and are precisely estimated: consumers dislike high prices and large distances to stores, and prefer greater THC and CBD potency. Extracts are the most preferred category, followed by solid edibles, usables, and liquid edibles. The nesting parameter is about 0.65, which suggests a high degree of substitution between product categories within a store, but also suggests some degree of substitution across stores [43]. Given that I aggregate products up to the category level to avoid extremely small market shares, the nesting parameter estimate only measures the degree to which consumers substitute across product categories and does not reflect intra-category substitution. However, intra-category substitution will be observed through the product category dummies.

Based on the demand estimates, I can compute price elasticities and travel costs, shown in Tables 11 and 12, respectively. Price elasticities are similar to those observed in the

[43] This is consistent with anecdotal evidence from store managers that substitution is mainly along product categories: if a consumer usually purchases a specific kind or brand of usable, he/she is likely to switch to a different usable in the presence of a price change, instead of switching to a different product category.

Table 1.10: Demand Estimation Results

Variable	NL1
Price	-0.116^{*}
	(0.0049)
THC %	0.015^{*}
	(0.0025)
CBD %	0.05
	(0.0123)
Usables	−0.587
	(0.407)
Inhalables	1.392
	(0.397)
Solid Edible	−0.372
	(0.563)
ρ	0.651
	(0.006)
Dist	−0.0014
	(0.0007)
Dist*log(PopDen)	−0.036
	(0.0004)
Π_1	−0.0019
	(0.0004)
Π_2	0.178
	(0.0071)
Π_3	−0.104
	(0.0068)

literature for cannabis products, albeit slightly higher for extracts and edibles. Elasticities are slightly lower for usables, the bulk of the products in the dataset [44]. Travel costs are similar but slightly greater than similar work such as Thomas (2019). This suggests that consumers are willing to pay $2.75 to avoid travelling 1 mile, which is a significant percentage considering that the median price per gram for a usable type product is $12 [45].

Table 1.11: Elasticities

	Usables	Solid Edibles	Inhalables
10%	-2.47	-9.69	-15.32
25%	-1.14	-7.60	-12.06
Mean	-1.22	-6.33	-10.26
50%	-0.70	-5.82	-9.56
75%	-0.44	-4.53	-7.85
90%	-0.3	-3.49	-6.38

Table 1.12: Travel Costs ($ per mile)

10%	1.62
25%	2.24
Mean	2.52
50%	2.75
75%	2.93
90%	3.04

At median census tract population density of 2657 people per square mile, this suggests a median travel cost of $2.75 per mile.

[44] One reason for this similar but slight discrepancy in elasticities with the related literature is due to the fact that I use the first 18 months of the data rather than the last 6 months. Products that require more processing appear later in the market, so the early stages of the market feature mostly usables, meaning less substitution to other categories.

[45] This is consistent with anecdotal evidence that consumers greatly value convenience. Interviews with consumers in some of these stores report perceiving these retailers as neighborhood shops and having some knowledge about prices in the black market.

1.8.2 Unobserved Marginal Costs Estimates

Using the Nash-Bertrand pricing first-order conditions, I back out the unobserved marginal costs. Figure 7 shows kernel density distributions of retail prices, observed marginal costs, and unobserved marginal costs [46]. I use the combined marginal costs and its distribution to compute retailers' profit functions when deciding where to locate and whether to apply, respectively. About 13 percent of unobserved marginal costs are negative, with the majority of the negative unobserved marginal costs under $5 per unit. However, only 5 percent of combined marginal costs are negative. One potential explanation for this apparent anomaly is that several retailers reported losing money during the early stages of the market, using their own funds to pay bills and keep the store open with the expectation that the market would grow over time [47].

1.8.3 Location Fixed Costs Estimates

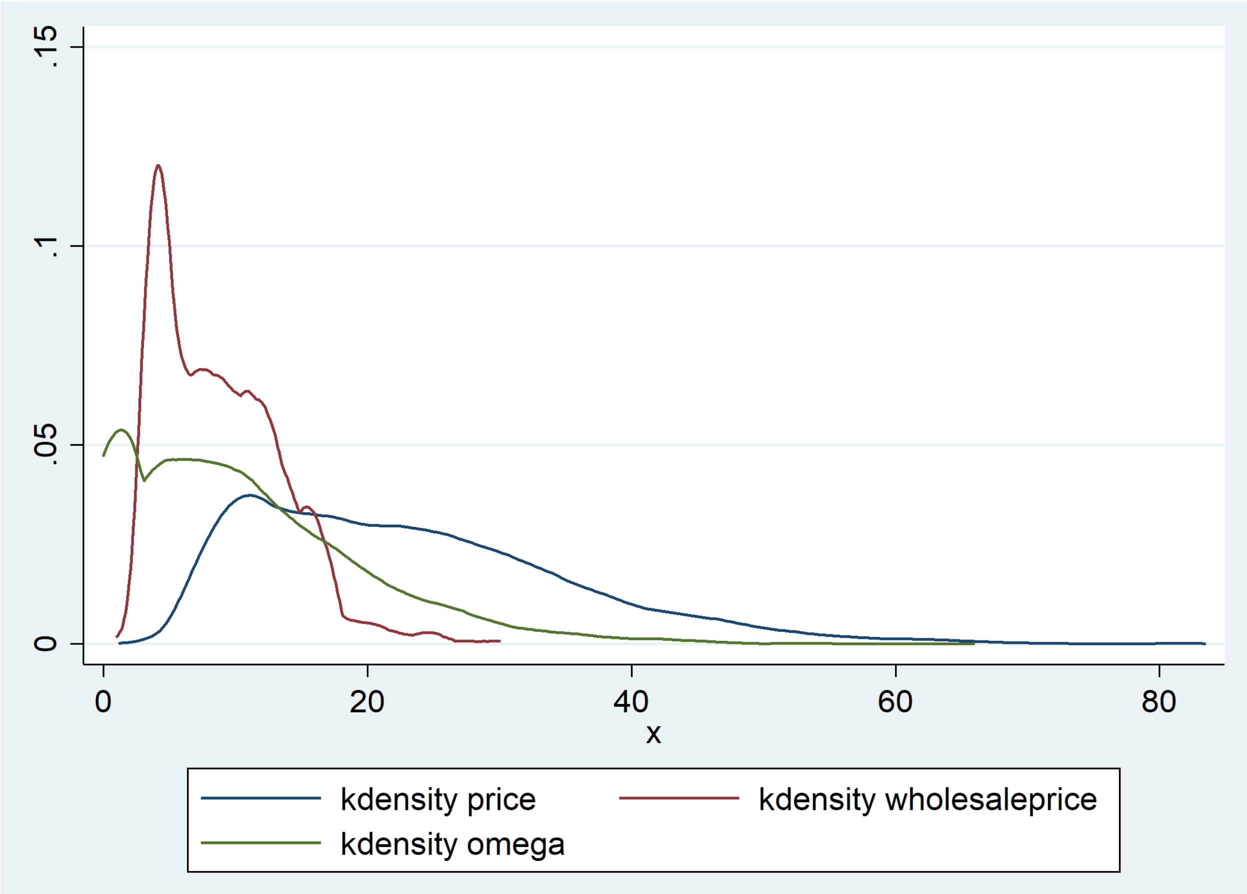
I use the demand and unobserved marginal cost estimates to compute the alternative variable profits for all the possible location configurations for firms in each location set in the state. Differences in variable profits will be due to the distance and price channels: the model predicts that firms closer to consumers should bring more profits and firms locating closer to other firms should lead to lower prices. Combined, the prediction on the sign is ambiguous. Figure 8 and Table 13 show the distribution of location-specific fixed costs. Since the closest analogue of these costs to a real-life economic measure is the cost of retail space rental, I normalize the costs to monthly dollars per square foot by assuming the average store size is 1900 sq ft [48]. The median cost of retail space is $3.58 per square foot, the mean is $5.79 per square foot, the 25% is $1.99 per square foot, and the 75% is $7.25 per square

[46] I censor any negative value up to 0 in the figure for clarity purposes.

[47] This prediction has been proven right: the market has substantially grown since 2017 levels.

[48] I use the website https://www.thebalancesmb.com/what-it-costs-to-rent-a-building-space-2890493 and compare the suggested values with actual retail space costs in Washington State from LoopNet, a retail space leasing search engine.

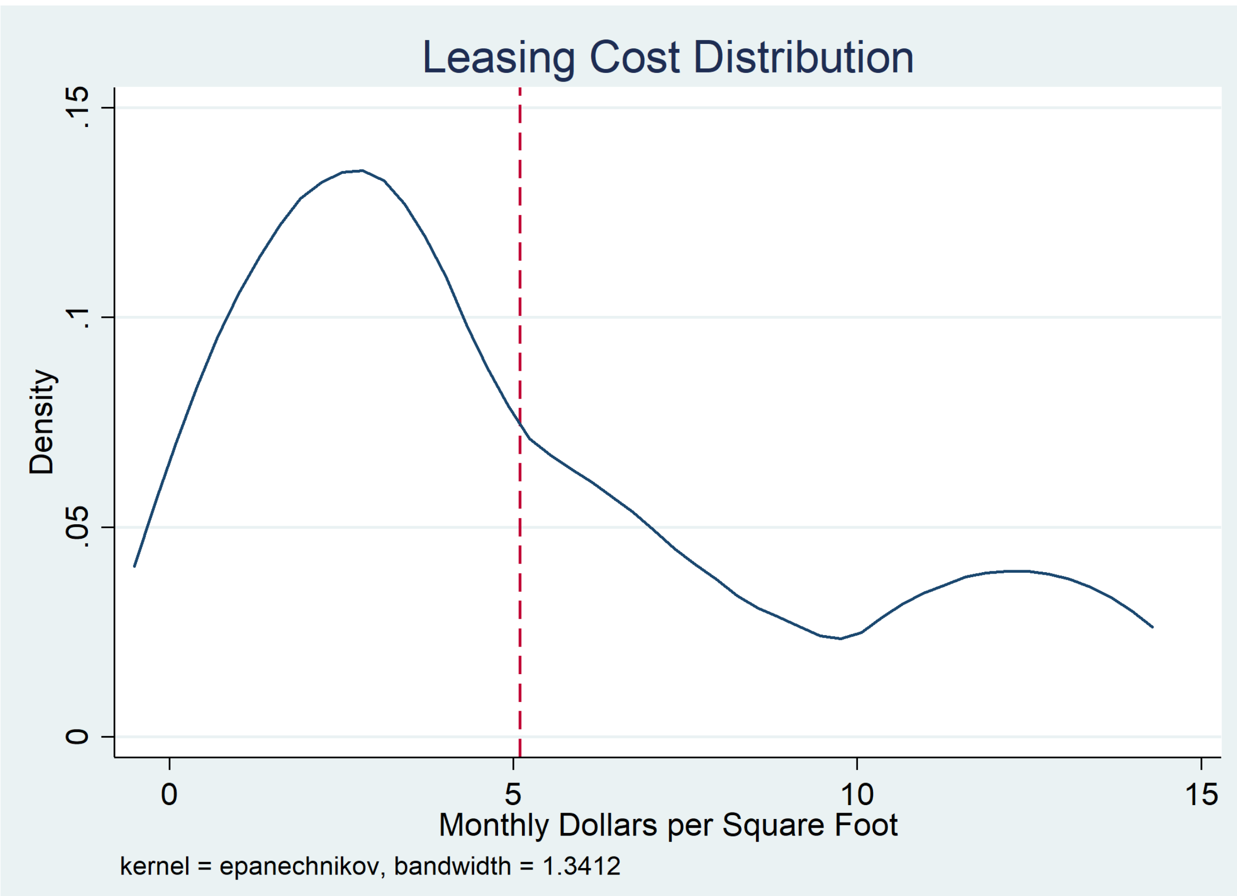
Figure 1.7: Distribution of Marginal Cost Estimates



This figure shows the distributions of the retail price, the wholesale price, and the unobserved marginal costs estimates. I winsorize any negative values of ω to 0 for clarity purposes.

foot. These estimates are in line, albeit slightly greater, with retail space rental reports from search engines such as LoopNet of what to expect to pay, depending on the location of the store: most retail locations of such a size appear to be between $1 and $4 per square foot, monthly. One potential explanation for the slightly greater magnitudes in my estimates, especially at the right tail, is the fact that cannabis retailers were not able to obtain leases for retail space that had a mortgage through a bank, so in practice, a substantial percentage built their establishments from scratch with their own funds or through types of financing associated with higher interest rates.

Figure 1.8: Distribution of Monthly Leasing Costs



This figure shows the distribution of monthly retail space leasing costs assuming the typical retail store has 1900 sq ft. The mean is $5.79 and the median is $3.58 per square foot. I winsorize the 90% percentile, $12.95, in the figure for clarity purposes.

Table 1.13: Distribution of Location Fixed Costs Estimation Results

10%	1.43
25%	2.00
$Mean$	5.79
50%	3.58
75%	7.25
90%	12.96

This table shows the estimated distribution of monthly location-specific fixed costs, normalized to dollars per square foot. Intuitively, we can interpret this as the cost to rent retail space.

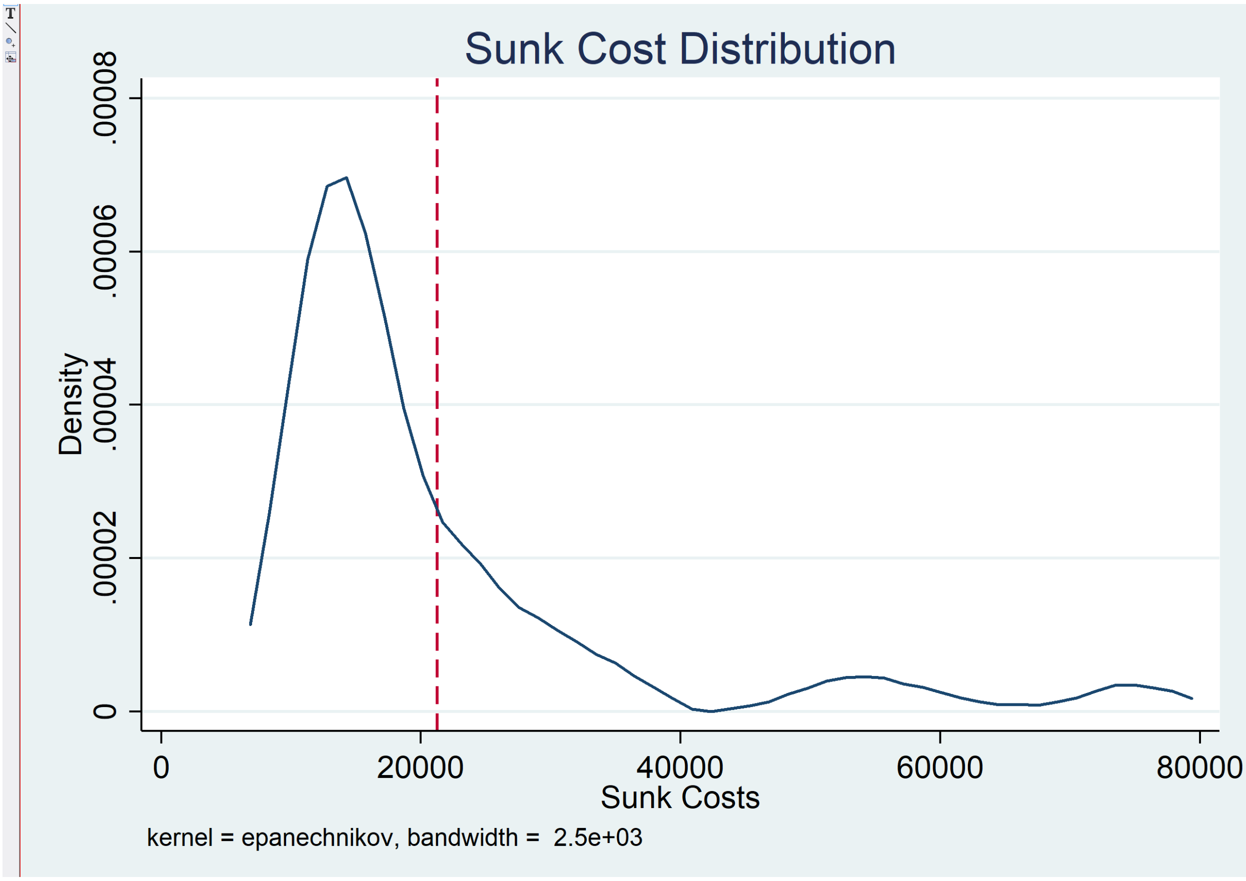
1.8.4 Sunk Cost Estimates

Figure 9 and Table 14 show the distribution of the one-time sunk costs of applying to the market. Intuitive, the sunk cost estimates reflect the opportunity cost that comes with investigating whether entering the market is economically worthwhile: doing market research, developing relationships with potential partners, find a retail space, as well as developing a brand and letting potential customers know of a coming store. The mean is $21,260, the median is $15,530, the 25% percentile is $12,794, and the 75% is 22,541. While it is not straightforward to compare these values with observed data, the estimates appear reasonable, considering that I assume that even firms that apply but do not get a license also pay this sunk cost. The closest existing estimates of fixed costs for this industry come from Thomas (2019), which finds bounds for fixed costs of retailer entrants. My estimates are almost half, which is not surprising considering her measures are closer to firms' operating costs, whereas I also measure the sunk costs of those who did not obtain a license and thus were never active in the market.

1.9 Counterfactuals

I conduct the counterfactual policy scenario of relaxing location restrictions around sensitive-use areas to 100 feet.

Figure 1.9: Distribution of Sunk Costs



This figure shows the distribution of one-time sunk costs for applicants. The mean is \$21,260 and the median is \$15,530.

Table 1.14: Distribution of Sunk Costs of Entry Estimation Results

10%	11,182
25%	12,794
Mean	21,260
50%	15,530
75%	22,541
90%	35,370

This table shows the estimated distribution of one-time sunk costs for applicants that consider obtaining a license to operate in the market. Intuitive, we can interpret these sunk costs as the opportunity cost of entering the cannabis market.

This involves increasing the number of available locations in a jurisdiction/location set while keeping the number of licenses fixed. In my model, firms that received a license have a fixed set of locations to choose from in their set $\mathcal{A}_{fm}$. Within this set, not all locations were available in the baseline model, since I exclude census tracts whose schools are closer than 1000 ft from the census tract centroid. For this counterfactual, I consider all census tracts within this location set where its schools are further than 100 feet from their population-weighted centroid. To keep the model computationally feasible, 20 locations per location set/jurisdiction is the upper bound of available locations. When estimating the model, the number of available locations was always less than 20.

The process to find the counterfactual locations would consist of solving the model from the beginning and recomputing the equilibrium of the game, since more locations becoming available means that jurisdictions may become more profitable, so more potential firms may apply. I start with the baseline, observed number of applicants, and let the entry equilibrium run in the population-driven order, meaning that the most populous jurisdictions consider an additional applicant first, and within a jurisdiction, the most populous location sets consider an additional applicant first. While expected profits for all jurisdictions and location sets are non-negative, I add an additional applicant, and continue until a jurisdiction/location set does not find it profitable to consider an additional applicant. This may lead to more jurisdictions binding. For nonbinding jurisdictions that consider an additional applicant, I simulate an additional firm. For jurisdictions that hit their license cap, I consider an additional applicant but do not simulate an additional firm's characteristics because no more firms can enter into the second stage. Instead, the additional applicant weighs down the expected profits of the first stage, since more applicants decreases the probability of any one applicant receiving a license. Once licenses are given out, the location game is played with the now larger set of locations. Once the locations are chosen, we plug the new locations into the housing model to calculate the new externality measure.

Before calculating the entry equilibrium, I start letting k_j equal the observed number of licensed firms in each location set, like a rational expectations setting. Given $k_j, \bar{n}_m, \sum_{LS} n_{LS}$, the only unknown is n_{LS}, the number of applicants in each location set, so I back it out through linear systems of equations. I perform a sanity check after calculating n_{LS} to make sure that the k_j terms these numbers of applicants add up to the licensed number of firms in the jurisdiction. For the great majority of cases, $\sum_{LS}[k_{LS}] = \bar{n}_m$. However, this is not a mathematical result since as the number of rounded up/down terms increases, the likelihood of going over $\bar{n}_m$ increases. To maintain the equality, I tweak how k_j is computed by assuming that, in the event of the equality not being satisfied, the least populated location set breaks the tie by having one fewer applicant: first, I compute k_j as in the model section. If after summing the k_j terms up, they add up to $\bar{n}_m$, leave that jurisdiction as is and move on. If the terms do not add up, remove one expected license from the least populated location set within that jurisdiction. This process is repeated until the equality is satisfied.

1.10 Counterfactual Results

I show the welfare measures from the baseline, status quo scenario versus the welfare measures from relaxing location restrictions down to 100 ft. Table 15 displays various measures of welfare in the baseline scenario of 1000 ft restrictions and in the counterfactual scenario of 100 ft restrictions for King County [49]. The sign of the changes in each individual welfare measure is expected: consumer surplus increases from \$17.1 million to \$26.9 million, firm profits increase from \$4.2 million to \$6.5 million, negative resident externality is exacerbated from -\$23.8 million to -\$25.7 million, sales tax revenue increase from \$3.1 million to \$4.8 million due to quantities increasing, and property tax revenue decrease from -\$11.3 million to -\$12.2 million.

[49] I provide counterfactual welfare measures for the entire state as well, shown in Table 16, except for statewide resident externality measures: I only have property data for King County.

Table 1.15: Counterfactual: Relaxing Location Restrictions to 100 ft, King County

	Baseline	CF	% Change
Consumer Welfare ($)	17,111,019	26,909,987	57.27
Sales Tax Revenue ($)	3,147,136	4,796,784	52.42
Quantity Sold	453,598	693,753	52.85
Firm Profits ($)	4,229,225	6,565,636	52.72
Resident Externality ($)	-58,747,056	-63,373,879	-7.88
Property Tax Revenue ($)	-11,300,574	-12,190,588.5	-7.87
AvgPopDen	3680	7368	100.22
MedianPopDen	2294	5871	155.92
PopDen25	280	3385	1100.09
PopDen75	5415	9480	7.51

Table 1.16: Counterfactual: Relaxing Location Restrictions to 100 ft

	Baseline	CF	% Change
Consumer Welfare ($)	46,802,646	84,319,356	80.16
Sales Tax Revenue ($)	9,539,400	17,928,194	87.94
Quantity Sold	1,455,036	2,742,174	88.46
Firm Profits ($)	12,945,754	24,307,853	87.76
AvgPopDen	3710	3248	-12.45
MedianPopDen	3015	2215	-26.53
PopDen25	510	353	-30.78
PopDen75	5202	4706	-9.53

On net, both resident surplus and tax revenues are less negative [50] than in the baseline measures. Overall resident surplus changes from -$6.8 million to $1.1 million and overall relevant tax revenues increase from -$8.1 million to -$7.4 million. This means that from the point of view of a regulator or social planner that takes into account both those that obtain

[50] On the resident side, residents now perceive a surplus.

utility from the market's products and those that receive a disutility from having the market close to their homes and schools, the gains for consumers offset the losses for residents. The same pattern appears for tax revenues: the stores impose a negative externality on property tax revenues, but giving them more options to locate leads to sales tax revenues that offset any losses from property taxes [51].

One reason behind the net welfare impact on residents for this policy scenario is the role that travel costs play in consumers' utility functions. The bottom half of Tables 15 shows summary statistics of the distribution of the population density of the census tracts chosen by the firms in King County. For King County, the distribution of population density for chosen location shifts rightward, meaning that at all levels of the distribution, firms locate in denser locations. Locating near denser areas corresponds to more consumers being reached, which can lead some consumers to substitute from the outside option to the inside options of the market. The more dense locations, combined with the importance of travel costs as shown in Table 12, explain the large increase in consumer surplus. An interesting pattern that appears in the counterfactual policy scenario is that even though urban areas display denser location choices, the pattern is reversed for rural areas and overall in the state. The bottom half of Table 16 shows summary statistics of various levels of the distribution of population density for location choices in the entire state: compared with the baseline, counterfactual locations are overall less dense. This is not surprising considering that travel costs are exacerbated by population density: in less dense areas of the state, the travel cost is not as big of a deterrent for consumers so firms in general prefer to locate farther from each other.

In summary, relaxing location restrictions around sensitive-use areas to 100 feet, when weighing both consumers and residents equally, leads to net welfare and tax revenue

[51]The caveats on calculating resident surplus without a full-blown model of the housing market are explicitly stated in the Appendix.

improvements with heterogeneous impacts on the individual groups studied. Consumers are better off, firms are better off, and residents are worse off. More sales tax revenue is collected but less property tax revenue is collected. A social planner that more heavily weighs the welfare of a particular group may obtain a different net welfare effect: for example, a state governor that places a greater weight on residents may place little weight on consumers of a potentially habit-forming and addictive substance but heavy weight on residents, leading to an opposite conclusion.

1.11 Conclusion

This paper is a case study of how local governments and policy makers can harness the power of market structure and firms' endogenous response to regulations to yield desirable results while minimizing the array of undesirable outcomes. I study the impact of location restrictions on recreational cannabis retailers in Washington State on residents, consumers, and taxation. I first show reduced-form evidence that cannabis retailers act as a disamenity when close to homes and to their assigned schools. Then, I develop and estimate a model of firm entry and location and consumer demand to analyze the role of various license and location restrictions on firms in mitigating externalities to residents. I then use these estimates to conduct counterfactual land-use policies such as relaxing the location restrictions.

I find that relaxing location restrictions around sensitive-use areas from 1000 ft to 100 ft benefits consumers and firms but harms residents, but on net, leads to welfare and tax revenue improvements. While the restrictions advocates' concern of potential exposure of cannabis to minors plays an economically significant role for households when determining where to buy a property, especially when cannabis retailers enter near properties' assigned schools, these negative impacts are offset by the gains that consumers obtain from a less regulated market. Anecdotal evidence from town hall debates, which skews toward supporting more stringent regulations, is unlikely to match the direction of the welfare effects found in this study due to not fully accounting for all affected parties from land-use policies.

Some regulations that can be studied with the framework described in this project are various levels of buffer stringency for location restrictions, stricter dispersal restrictions, allowing the creation of cannabis business districts by confining the market to specific areas of cities, various stringency levels of licensing regulations, and welfare maximization through a social planner's problem. Concurrent work in Larsen (2020*a*) incorporates the negative externality imposed on homebuyers in more comprehensive ways such as allowing for resident sorting, heterogeneous impacts, and varying beliefs about how the market will evolve in the future, all of which are outside the scope of this paper. A few interesting future directions for this topic are more thorough analyses of housing as an investment that evolves over time akin to Bayer et al. (2016), assessing the risks of cannabis consumption through psychological addiction, and modeling how cities endogenously determine amenity provision.

The issues surrounding land-use regulation in the Washington State cannabis industry are paramount not just for the states that are in the process of legalizing cannabis for production and consumption, but for any setting in which land-use regulations affect market structure [52] and are imposed with the goal of mitigating some kind of externality. Reconciling the existence of nascent cannabis markets with the prevailing norms and beliefs of citizens as it impacts facets such as urban planning and housing as an investment device is just one of the new issues to be encountered when bringing a market from the shadows into the light.

[52] A salient, recent example is the role of short-term bans for Airbnb in residential zoning areas.

Chapter 2

A Discrete-Choice Approach to Measuring (Dis)amenity Value for Homebuyers

2.1 Introduction

The history of urban development in recent US history has been one of a tug of war between those that seek more lax regulations to allow building and development, and those that seek additional regulations to preserve their contemporaneous neighborhoods. Among the former group, there are land developers, affordable housing advocates, and business owners. Among the latter, homeowners and historical neighborhood associations. One recent case study of the ubiquitous tension between development and preservation is the creation of the recreational cannabis market in Washington State. The recreational cannabis legalization referendum in Washington State included location restrictions on where cannabis retailers could set up shop, and the main goal of these regulations was to minimize cannabis exposure to minors.

A question of interest is measuring residents' utility for cannabis retailers in light of the potential exposure to minors, and how knowing these preferences can be used to design optimal zoning policy for sin good businesses, which are desirable for local governments due to the substantial tax revenues derived from them. This question is timely because many states are considering legalizing and regulating the production and sales of recreational cannabis, so devising sensible urban planning policy that does not handicap the industry is of first-order importance.

In this paper, I measure homebuyers' preferences toward cannabis retailer proximity to their homes and their nearby sensitive-use areas via a discrete-choice framework. I find that, on average, people dislike having cannabis retailers near their homes and schools, but that the impact is heterogeneous, mainly falling along a children- no children boundary, with families with minors being the demographic most negatively impacted. I find that relaxing location restrictions around sensitive-use areas from 1000 feet down to 100 feet would decrease homebuyer surplus by about 65%. To conduct this exercise, I first estimate a housing demand model, plug in the alternative locations for cannabis retailers obtained in Larsen (2020*b*), and compute the resident surplus measures based on sorting on the intensive margin of house purchasing decisions. The findings are qualitatively in line with the hedonic method used to measure residents' negative externalities in the aforementioned paper, but are greater in magnitude since they allow for sorting while the previous work did not. Regardless of the method and that sorting on the extensive margin is shut down [1], the harm from allowing the market to expand beyond the status-quo allowed locations would not offset the benefit that an expanded market brings to consumers.

Buying a house is one of the most important decisions an individual or household will make in their life. There is generally a period of saving, searching, negotiating with real estate agents, and the mortgage can last up to thirty years. Households submit an application to be approved for a mortgage and the government monitors any potential acts of discrimination toward homebuyers. The housing market is one that is characterized by slow supply increases, numerous supply restrictions, and a pervasive desire by homeowners to use their home as an investment vehicle, and ensuring their value goes up, not down. For this last reason, incorporating disamenities near homes may lead to opposition by home buyers and homeowners, since a decrease in the value of their typically largest investment may take a long time to recoup. It has been argued that, at least for a substantial percentage

[1] Opening the extensive margin channel means allowing the housing supply decision to be endogenous rather than fixed.

of the population, cannabis retailers fall into the disamenity category, together with landfills, high-crime areas, and industrial zones.

The insights gained from this exercise and the framework can be used to inform both market design for current and future cannabis markets as well as any market or urban amenity that may be imposing a negative externality on residents. Zoning and other land-use policies considered by policymakers can be used in conjunction with more traditional economic policies such as taxation and entry restrictions to devise markets that can make the most number of agents satisfied while abating any negative impacts.

2.2 Contribution

2.2.1 Measuring Urban Amenities

First, I contribute to the urban economics literature on measuring urban amenities and disamenities. Bayer, Ferreira and McMillan (2007) develop a model to better estimate residents' preferences for amenities in urban areas by combining both a regression discontinuity and a discrete-choice model to study to what extent residents value high-quality schools, Greenstone, Hornbeck and Moretti (2010) use a hedonic model to measure the impact of polluting energy plants on residents, and Sinha, Caulkins and Cropper (2018) compare how hedonic and discrete-choice models perform in estimating residents' preferences toward amenities. Hedonic regression papers are only accurate in measuring the average valuation for amenities, but in settings where the valuation for an amenity is heterogeneous, other methods may be necessary for a more complete picture. Discrete-choice models that measure amenitity values like Bayer can tackle the heterogeneity, but caution must be exercised when aggregating housing types. I develop a model of housing demand within a discrete-choice framework to measure the heterogeneous impact of cannabis retailers, considered a disamenity to some people, on residents and find that residents living in areas with mainly adults without children consider it an amenity and residents living in areas with adults with children consider it a disamenity. These findings can help inform policy that aims to mitigate the negative externality that a cannabis retailer may impose on residents by allowing retailers to locate far from areas with greater percentages of minors.

2.2.2 Zoning and Urban Planning Policy

I contribute to the urban economics literature on zoning and urban planning policy. Recent work to measure the value of zoning on economic activity has Turner, Haughwout and van der Klaauw (2014) studying land-use reform on the value of the usable land and Shertzer, Twinam and Walsh (2018) studying how zoning has shaped long-term urban economic activity (or lack thereof) on specific neighborhoods in Chicago. Cities across the world face questions on where to allow certain businesses to operate and devise zoning and other land-use regulations to study how a location restriction on cannabis retailers affects residents and how alternative land-use policy can mitigate or exacerbate the externality this type of business imposes on residents. I find that relaxing location restrictions around sensitive-use areas from 1000 feet to 100 feet makes residents on average worse off by decreasing the resident surplus they obtain, but groups divided by whether they have children or not, measured by the percentage of underage people in their census tract, face heterogeneous impacts. The status quo restriction appears to mitigate a resident externality that is mostly perceived by residents with minors, which is in line with the original purpose. When the economic analysis of this project is tied with Larsen (2020*b*), I find that while the resident negative externality is exacerbated under a more relaxed policy scenario, the positive effects of a broader market more than outweigh the costs imposed on residents, if I assign equal weights to each surplus measure. This means that if a policymaker were to treat residents' and consumers' equally, the benefit of consumers would outweigh the concern of residents and to justify the existing policy, more weight would have to be applied to residents. Generally, local policymakers make policy decisions by assessing the existing cost-benefit analysis of a proposed policy under their set of preferences, and this analysis is supposed to provide some insight into a land-use regulation that has become ubiquitous as more states legalized cannabis for recreational purposes.

2.2.3 Intersection of Industrial Organization and Urban Economics

Second, I contribute to the growing body of empirical work at the intersection of industrial organization and urban economics. Recent work by Calder-Wang (2020) studies the heterogeneous impact that Airbnb had on the housing rental market by developing a model of both long-term and short-term rental demand and supply, and finds that the losses that residents perceive through increased rent prices are greater than the gains that the hosts perceive from offering their units as Airbnbs. Almagro and Dominguez-Lino (2020) studies the relationship between location sorting and how Airbnb hosts decide to provide short-term rental in certain areas according to resident preferences. Nishida (2014) measures the costs of zoning regulations for convenience stores in Japan and finds that absent the regulations, there would be greater firm entry and sales. Other work in this intersection mainly studies the impact of spatial differentiation on market outcomes, with papers like Orhun (2012), Zhu and Singh (2009), Seim (2006), and Datta and Sudhir (2012). There is also work on the relationship between zoning and competition with papers like Ridley, Sloan and Song (2010) and Picone, Ridley and Zandbergen (2009). My contribution consists of taking a discrete-choice framework from the empirical industrial organization literature and applying it to a land-use policy concerning how residents value cannabis retailers near their homes and schools. The model is static because the shops open up in a short period of time, so unlike the Bayer et al. (2016) paper on dynamic housing supply, I focus on the short-run valuation of properties.

2.2.4 Impact of Cannabis Markets

Lastly, I contribute to the recent literature on the impact of cannabis markets on broader economic outcomes. Cannabis has been touted as an important source of tax revenue for states due to the widely used nature of the drug but no legal market from which to extract taxes. Hollenbeck and Uetake (2021) study the link between tax rates and firms' price-setting power in the Washington State cannabis industry and find that the current 37% tax rate is lower than optimal from the point of view of a tax revenue maximizing policymaker. Their work is particularly important since it studies questions of pass-through and taxation in a scenario with local monopolists with substantial price-setting power. On the other side of the political spectrum, communities have been long concerned about facilitating drug exposure to minors, and Thomas and Tian (2019) find, through a hedonic framework, that property values fall by about 5% when a cannabis retailer opens near residents' homes. While Larsen (2020*b*) expands on Thomas and Tian (2019)'s hedonic modeling to include other sensitive-use areas and models the industry's market structure, this project studies the same question under a discrete-choice framework, which can provide insight into the potential heterogenous impact of nearby cannabis retailers.

2.3 Data

I combine data from various sources to obtain a sample of the houses purchased, information on homebuyers, election results, and neighborhood and housing characteristics. The backbone of the analytical sample is the King County Tax Assessor Property Sales Data, which has information on all sold properties in King County. This dataset includes property sold price, property characteristics such as number of bedrooms, number of bathrooms, square feet, and a tax-assessor-provided grade of quality. The data only provides the address of the parcel, so I geocode the properties' addresses using the Texas A&M Geocoding Services to obtain the latitudes and longitudes. First, I conduct an exploration of classifying properties into housing types. It is not clear ex-ante how to split up housing or if the Calder-Wang (2020) method is satisfactory for my setting. Her data is from New York City, which has more housing than King County, so I must use fewer variables to avoid extremely small market shares. I classify properties according to 27 housing types, based on three housing characteristics: three tiers of square footage, three tiers of number of bedrooms, and three tiers of quality grade. I then aggregate the data up to the year-census tract-housing type level, the level of observation used for the empirical section of the paper.

Since the paper aims to measure the externality that cannabis retailers impose on residents by measuring residents' choices in property through changes in property values and the best available data is property sales data, I model homebuyers' decisions to purchase a property. To achieve this, I use data from the Home Mortgage Disclosure Act, which includes information on all individuals to apply for a mortgage and features applicants' income, race, and census tract. I use data from the 2014 ACS to gather information on the properties' neighborhood characteristics and the homebuyers' neighborhood characteristics. I also augment homebuyers' and neighborhoods information with the i-502 referendum results to measure attitudes toward cannabis legalization. Finally, I generate distances between census tract centroids and nearby cannabis retailers.

2.4 Model

2.4.1 Housing Demand

I adapt the long-term rental housing demand model from Calder-Wang (2019) to my current setting of long-term home buyer demand.

2.4.1.1 Market Definition

A prospective homebuyer considers to make a discrete choice from several housing types in a number of nearby neighborhoods. Each type of house h is characterized by the neighborhood n, a census tract, where the property is located, by its physical characteristics such as the number of bathrooms and bedrooms, the property's age in terms of the decade built, and tax assessors' measures of the type and quality. Within each type h, there are N_h units that are equal up to an idiosyncratic shock $\epsilon_{i,j}$.

Since there is only a median of about 12 miles between the homes that recent home buyers purchased and the homes they moved from, I assume home buyers consider housing types in neighborhoods within 10 miles of their neighborhood n. This effectively creates choice sets for home buyers. A home buyer's choice set is defined as $\mathcal{B}_i = \{(h, n) | d_{n_i n_h} \leq r_i\}$ where $d_{n_i n_h}$ is the distance between the population-weighted centroid for homebuyer i's neighborhood n_i and the housing type h's neighborhood n_h, and $r_i = 10$ is the maximum distance they are willing to search in miles. For smaller cities, this mostly encompasses the entire urban area and for bigger cities, it encompasses a substantial percentage of the urban area.

2.4.1.2 Model Specification

The utility of home buyer i from purchasing a property j of housing type h is:

$$u_{i,j} = \alpha_i p_h + \beta_i X_h + \xi_h + \epsilon_{i,j} \tag{2.1}$$

where p_h is the average price of housing type h, X_h includes physical characteristics such as number of bedrooms, number of bathrooms, sq ft, building age, building type, condition [2] and neighborhood characteristics such as census-tract-level i-502 referendum results, percentage of college-educated households, race percentages, income, and proximity to nearest retailer, to nearest sensitive-use area (SUA), and between the assigned SUA and the SUA's nearest retailer. There is also a demand-side term ξ_h that home buyers observes

[2] An official designation of quality given by the tax assessor.

but that the econometrician does not. Finally, each individual receives a type I extreme value error $\epsilon_{i,j}$.

For demographic characteristics of home buyers, I use data from theHome Mortgage Disclosure Act, which includes the race, income, and census tract of the individuals [3] that request a mortgage. I also complement this dataset with other census-tract demographic characteristics from the ACS data, especially the number of children and percentage of families with children in the home buyer's census tract.

Each home buyer i purchases a property j by maximizing her utility by comparing all available options :

$$y_i = j \iff u_{i,j} > u_{i,-j} \tag{2.2}$$

The group of home buyers that purchase type h is the group of home buyers that purchase any property j of type h:

$$A_h = \bigcup_{j:h(j)=h} \{z_i, \epsilon_{i,\cdot} : u_{i,j} > u_{i,-j}\} \tag{2.3}$$

The demand for property types h is calculated by summing up the home buyers that have housing type h in their choice set:

$$D_h(p_h, p_{-h}) = \int_{A_h} dP(\epsilon) dP_D^*(z) \tag{2.4}$$

with P_D^* being the distribution of demographic variables of home buyers.

2.4.2 Housing Supply

Supply of housing types is fixed at N_h. The prices clear according to this fixed supply:

[3] I use the census tract where mortgage applicants resided at the time of applying for a mortgage.

$$\forall h : D_h^L(p_h^L, p_{-h}^L) = N_h \tag{2.5}$$

N_h is the number of properties that were sold for a particular housing type-census tract-year. The outside option is to stay at their current location and not purchase a house. The fixed supply assumption means that if we conduct a counterfactual policy that leads people to choose different housing, the endogenous sorting process on the intensive margin [4] means that prices will adjust so that the market clears.

The data used is almost identical in nature to the data used in Bayer et al (2016). A key distinction from the literature is that I assume the supply of housing is the housing that is available for sale, not the entire supply of housing. This is in line with the goals of the paper and with the data limitations: modeling decisions for homebuyers [5], not renters, and using the property sales data. Assuming the latter would require either including renters as 'consumers', which would lead to extremely small market shares and thus make the estimation unstable. I model the characteristics of prospective homebuyers from the set of mortgage applicants in the HMDA data and restrict the available housing to the houses that sold each month. Thus, the market clears in the model.

2.5 Housing Demand Estimation

The estimation procedure broadly follows Calder-Wang (2020), which follows (Berry, Levinsohn and Pakes, 1995), Berry, Levinsohn and Pakes (2004), and Bayer, Ferreira and McMillan (2007). Data on housing types market shares construct macro moments, which

[4]By intensive margin, I mean that home buyers may choose more of one specific housing type, even if the number of properties in a housing type remains fixed. The extensive margin in this exercise would be more housing being offered by home sellers and more home buyers than was observed in the data, something that is outside the scope of this paper.

[5]The idea is that homebuyers arguably drive price changes due to disamenities, due to sorting, more than renters.

exploit the information on how home buyers substitute housing types. Data on demographic characteristics construct micro moments, which exploit the information in the similarity in demographic characteristics between home buyers' home census tract and the purchased home's census tract. First, I estimate the individual-level coefficients by exploiting the census-tract-level mortgage data. Second, I obtain the linear coefficients.

The utility can be broken down into two parts: one common to all home buyers and one specific to each home buyer i, which is a function of observables z.

The mean utility from housing type h is:

$$\delta_h = \alpha p_h + \beta X_h + \xi_h \tag{2.6}$$

The home buyer-specific part of the utility is:

$$\lambda_{i,h} = (\sum_k \pi_{\alpha,k} z_{p,i,k}) p_h + (\sum_k \pi_{\beta,k} z_{x,i,k}) X_h \tag{2.7}$$

where $z_{p,i,k}$ is home buyer i's race, income, and whether he/she has children, $z_{x,i,k}$ is the percentage of underage people in the home buyer's census tract, and X_h includes the distance variables from the census tract centroid to the nearest retailer and from the census tract's assigned school to its nearest retailer.

Let N_h be the number of properties for sale of type h. If the idiosyncratic shock ϵ is i.i.d. TIEV, we can construct the choice probabilities for home buyers:

$$Pr(y_i \in h; \delta_h, \pi) = \frac{N_h exp(\delta_h + \lambda_{i,h})}{\sum_{h'} N_{h'} exp(\delta_{h'} + \lambda_{i,h'})} \tag{2.8}$$

2.5.1 Constructing Moments and the Objective Function

First, I define moments to identify the mean values δ and the individual-level coefficients π. I have purchase choices at the individual-level, so I construct $1_{\{y_i \in h\}}$, which allows me to construct moments that match the market shares at the housing type-census-tract level s_h. In addition, I construct moments which equate the covariance of the property characteristics $X_{b,h}$ and the mean demographic characteristics z_k of home buyers that purchase h. For example, I equate the covariance of the square footage and the mean income of home buyers that purchase housing types with similar square footage. The moments that identify δ and π are:

$$\forall h : E[Pr(y_i \in h; \delta, \pi)] = s_h \tag{2.9}$$

$$\forall b, k : Cov(E[z_k | y_i \in h; \delta, \pi], X_{b,h}) = Cov(\bar{z}_{k,h}, X_{b,h}) \tag{2.10}$$

where the right-hand side is obtained from the data:

$$\hat{s}_h = \frac{1}{N} \sum_i 1_{\{y_i \in h\}}, \ \ \hat{\bar{z}}_{k,h} = \frac{1}{N} \sum_i 1_{\{y_i \in h\}} z_{i,k} \tag{2.11}$$

where $N = \sum_{h'} N_{h'}$. I match the model market shares to market shares observed in the data to back out the mean utility δ via the usual BLP contraction mapping:

$$\delta^{n+1} = \delta^n + ln(s) - ln(\hat{s}(\delta^n)) \tag{2.12}$$

Equation (2.9) means the model is supposed to match model market shares with observed market shares. The left-hand side is the probability that a homebuyer in census tract i purchases a property of type h, averaged over all the homebuyers in census tract i. To provide intuition on Equation (2.9), suppose a homebuyer has to decide between 5 houses, 3 of type A and 2 of type B. Further, suppose that the mean utilities for both types is the same, $\delta_A = \delta_B$. Suppose the homebuyer chooses a house of type A. Then, any differences in market shares should come from the preferences of the homebuyer in the census tract i for the individual-specific terms $\lambda_{i,h}$ and the supply of housing types that multiplies the exponentiated term. In fact, even if the entire base utilities for household i were the same, i.e. $\delta_h + \lambda_{i,h} = \delta_{h'} + \lambda_{i,h'}, \forall i$, the difference in market shares will be driven by differences in housing types fixed supply [6]. The same idea applies for the covariance moments.

Second, I construct the moment conditions that allow me to identify the linear parameters α, β, and the unobservable ξ_h. The market price p_h may be correlated with the unobservable ξ_h, so I use an instrument that exploits the housing characteristics space as in Bayer, Ferreira and McMillan (2007) and Calder-Wang (2020). The instrument consists of employing the property characteristics of similar properties in different neighborhoods. To measure the effect of housing characteristics on market price, I calculate new property prices by setting $\xi_h = 0$ and allowing the market-clearing equations for housing types to provide the alternative market shares. The moments are:

$$\forall h : E[Pr(y \in h; (p^{IV}, \alpha, \beta, \xi = 0, \pi, X^{exog}))] = s_h \tag{2.13}$$

$$\forall h : E[Pr(y \in h; (p, \alpha, \beta, \xi, \pi, X))] = s_h \tag{2.14}$$

$$E[p^{IV} X^{exog}] = 0 \tag{2.15}$$

$$E[\xi X^{exog}] = 0 \tag{2.16}$$

Constructing the alternative equilibrium price p^{IV} requires a supply-side pricing equation. Since this context features a fixed housing supply, the supply-side pricing equation is a market-clearing condition for all housing types. For each α, β, ξ, there exists a corresponding p^{IV}.

[6]Note that I am imposing market clearing for housing and that housing supply is fixed. As a thought exercise, suppose there is a single homebuyer in census tract i and that its base utilities (except logit errors) are identical for all its housing choices. Then, other homebuyers from other census tracts should have access to these 5 houses as well, such that the market clears. I do not currently allow fewer buyers than the number of available homes. An implicit assumption is that if that were the case, then the price should adjust to become an attractive option to other homebuyers. I allow potentially more buyers, and the difference is absorbed by the outside option. More details about the construction of the market share moments can be found in Calder-Wang (2020) and Berry, Levinsohn and Pakes (2004).

To obtain identification, I need that certain property characteristics X^{exog} be independent from the unobservable term ξ:

$$\xi \perp\!\!\!\perp X^{exog} \tag{2.17}$$

p^{IV} is obtained by making $\xi = 0$, p^{IV} is by definition uncorrelated with ξ. The challenge in this context is to find certain property characteristics that are plausibly independent from ξ. Bayer, Ferreira and McMillan (2007) suggest using a set of unchangeable characteristics of the total available properties like the number of bathrooms, number of bedrooms, building type, building age, etc. I exclude neighborhood demographics since these may be correlated with unobserved quality. The alternative price is obtained by resolving the market-clearing condition with only X^{exog}.

The demand coefficients and the price instrument are estimated jointly. The population moment conditions should equal 0 at the true parameters $\theta = \theta_0$:

$$G(\theta) = \begin{bmatrix} G_1(\theta) \\ ... \\ G_N(\theta) \end{bmatrix} = 0 \tag{2.18}$$

The GMM estimator is obtained by the expression:

$$\hat{\theta} = argmin_{\theta} \hat{G}(\theta)' \hat{A}^{-1} \hat{G}(\theta) \tag{2.19}$$

where $\hat{G}(\theta)$ and $\hat{A}$ are the sample analogues to $G(\theta)$ and A, respectively, and A is the moments' variance-covariance matrix. $\hat{A}$ is obtained with a 2-step procedure.

2.5.2 Caveats and Limitations

I describe a few caveats to the exercise conducted in the paper. First, I assume no dynamics, which may be important when considering housing as an investment as Bayer et al.

(2016) studies. Since the rise of cannabis retailers in Washington occurred over a short period of time, I use the changes in property values over a short time period to measure residents' attitudes. Using sales from before and after the market started, I can measure how property values capture residents' attitudes toward the existence and location of cannabis retailers and since a property is an asset, I can safely assume that the price reflects changes in its desirability and any changes are priced in as soon as they occur. I am assuming all dynamics in housing as an investment enters the housing sale price.

Second, housing transactions data may not be fully representative of the full sample of homeowners/residents. This may be not as innocous if renters also have an outsize impact on property values, or if their attitudes are markedly different from home buyers' attitudes. I lack the data to study renters' attitudes or how rent prices change due to this policy change. If we assume renters' preferences are exactly those of home buyers' preferences toward cannabis retailers, we could apply the results from this paper to all housing in King County.

Third, while I allow homebuyers to potentially choose a different housing type in counterfactual policy scenarios, I can't predict whether more or fewer homes may become available for sale. Thus, I am only able to capture changes on the intensive margin. Allowing more housing supply to become available is outside the scope of the current study but is a fruitful avenue for future research.

2.6 Results

I provide point estimates of the estimation procedure outlined in the previous section [7].

[7] Standard errors will be provided in a future iteration of this project.

Table 2.1: Demand Estimation Results

Variable	NL1
Price	-9.3853
Square Footage	0.198
Bedrooms	0.081
Quality	0.278
Distance Bin Home Retailer	0.576
Distance Bin Retailer School	0.629
Log Pop Den	-0.387
Underage	-2.482
$\Pi_{\beta,1}$ (Dist Home Ret * Underage)	-2.412
$\Pi_{\beta,2}$ (Dist Ret School * Underage)	-3.374
$\Pi_{\alpha,1}$ (Price*ShareWhite)	0.8673
$\Pi_{\alpha,2}$ (Price*Median Income)	1.6724
$\Pi_{\alpha,3}$ (Price*ShareYesVote)	-0.531

The signs of the point estimates are economically significant and make qualitative sense: people dislike higher prices, like more square footage, like more quality, and dislike denser areas. Regarding preferences toward cannabis retailers, people appear to like being close to a cannabis retailer if they do not have any children, but greatly dislike living near them if they do have children. The same pattern applies regarding living in an area where a cannabis retailer is near its assigned school. Demand becomes steeper as median income increases, which is consistent with the idea that richer home buyers prefer high-value housing. Using the average number of underage people in a census tract, the effect of having nearby cannabis retailers is negative, which is consistent with Larsen (2020*b*)'s hedonic results. The key difference between the hedonic analysis and the present analysis is that the demand estimates interpret home buyers' preferences beyond the price, which allow us to get a more complete picture of what heterogeneous home buyers like and dislike. The estimates appear to confirm what was discussed with real estate agents in the Seattle area: adults with children appear to be the demographic most concerned with cannabis retailer presence and may be the group most likely to perceive them as disamenities and move elsewhere. Adults without children, on the other hand, may perceive cannabis retailers as an amenity and value living close to one, and be indifferent toward having a cannabis retailer near their assigned schools.

2.7 Counterfactual Policy

In this section, I calculate the surplus that homebuyers obtain from the existing housing stock, and how this surplus changes when I consider the counterfactual policy of new cannabis retailer locations from relaxing the buffers around sensitive-use areas to 100 feet. I compute resident surplus via the familiar log sum formula. Note that in contrast with the hedonic resident externalities, in this exercise residents perceive a surplus from purchasing a property, but may receive a lower surplus than otherwise if they purchase near a disamenity.

Table 2.2: Counterfactual: Relaxing Location Restrictions to 100 ft, King County

	Baseline	CF	% Change
Resident Surplus ($)	18,321,859.3	6,350,245.4	-65.34

Table 2 shows the decrease in resident surplus from having cannabis retailers closer to homes and schools. Surplus decreases by roughly 65% and judging by the estimates, most of this decrease is driven mainly by increased retailer proximity to sensitive-use areas and increased retailer proximity to dense areas [8], which is where most people live and where most of the available housing stock is.

This surplus decrease is larger than the resident externality increase calculated from hedonic estimates in Larsen (2020*b*), which is consistent with the fact that the present exercise allows for homebuyers deciding to choose other housing when a certain area becomes too close to a retailer for their preferences. I would expect a future counterfactual exercise

[8]Cannabis retailers locating in dense areas is better for business but affects more residents.

that allows sorting on the extensive margin to have even larger impacts. However, whether resident externalities can outweigh the benefits of the market to consumers still appears unlikely. Policymakers could in principle use this framework and results to craft policy but the final decision should be determined by what the policymakers decide is more important for the city, and that decision may involve placing different weights on market and residents than weighing them equally.

2.8 Discussion

This paper is an empirical exercise to more thoroughly measure how people perceive a potential disamenity. Absent detailed survey data on Washington State citizens or more accurate measurements on how people felt toward the opening of cannabis retailers near their neigborhoods, I employ a discrete-choice approach to measure homebuyers' preferences in housing purchases near the beginning of the cannabis market. This approach allows me to measure heterogeneous preferences toward the proximity of cannabis retailers to homes and to their nearest schools. In addition, the exercise allows for endogenous sorting of homebuyers as retailers move closer to sensitive-use areas due to more relaxed policies. Without a model, any counterfactual outcome would ignore crucial sorting patterns of people and subsequent changes in price and housing availability. In this exercise, I open the sorting channel on the intensive margin by developing a model of homebuyer demand.

I compute resident surplus under the 2014 policy and under the counterfactual policy of relaxing location restrictions of cannabis retailers from sensitive-use areas down to 100 feet and find that resident surplus decreases by 65% when cannabis retailers are allowed to lcoate up to 100 feet away from sensitive-use areas, which opens up more locations for firms to open their establishments but are now closer to where more people live and closer to their assigned schools. The impact is heterogeneous and most negatively affects homebuyers from census tracts with greater percentage of underage people, i.e. areas with families with children. Homebuyers from areas with very small percentage of underage people, i.e. areas with adults without children, appear to perceive cannabis retailers as an amenity. On average, however, the impact is negative.

I list a few potential fruitful avenues for future research on measuring resident externalities. First, it is not clear how to aggregate housing so that current cutting-edge models of housing demand can perform satisfactorily. A method that is more streamlined and relies less of heuristics would be very useful to more easily apply off-the-shelf models to study housing demand. A rich enough dataset would be able to tell the researcher to what extent consumers perceive choices as substitutes, but the existing property sales data does not appear to be as rich to permit this.

Second, incorporating a model of housing supply would allow the researcher to measure sorting on the extensive margin. I currently allow sorting on the intensive margin but rely on fixed housing supply. Having additional data on the existing stock of housing and compare the existing total with the stock used for renting and the stock used for selling would lead to a model where homeowners decide to put their homes for sale if a disamenity appears close to their property and threatens to devalue its worth.

A third area of fruitful work is in comparing and contrasting homeowner preferences from renter preferences. I only have property sales data and since it is not clear how different these two sets of preferences are, I abstain from including the set of renters into the exercise. While one could argue that renters also perceive cannabis retailers as disamenities, it is not clear how differently they perceive price, and the calculus to both calculate and reconcile both sets of surplus is not clear without additional data and a model that includes both renters and buyers.

Chapter 3

Continuity and Change: The Role of Consumer Demand versus Inertia in Vertical Relationship Formations in a New Market

3.1 Introduction

How does a new market evolve? Which economic forces are important for the equilibrium of a market, and which are not? The dearth of new markets and the lack of data availability to analyze them from such early stages generally does not allow researchers to answer these types of research questions. This project has both features, which allow me to study how firms are subject to consumer demand forces and inertia when it comes to building relationships with suppliers and understanding their customer base. I also investigate how upstream and downstream firms coordinate supply decisions in vertically separated markets and which motives may drive the observed sorting patterns: in the Washington state recreational cannabis industry, producers appear to trade almost exclusively with at most one or two retailers in any given county. I provide a model of consumer and retailer endogenous response with link formation frictions that aims to provide structure for the economic forces at hand and to guide the empirical analyses.

Using comprehensive data on firm transfers, I answer the following questions: (1) do vertical relationships exhibit structural state dependence and if so, why? and (2) which economic forces are most important for retailers when approaching an equilibrium? The first question aims to test whether the observed sorting patterns occur out of state dependence with past trades or if the observed correlations are spurious or due to unobserved heterogeneity. Being able to discern between the two factors is crucial to understand whether firms obtain some value from the observed sorting patterns or if they enter into these arrangements merely out of randomness. The second question tests the degree to which consumer demand responses and inertia guide retailers' decisions as the market matures. I find that, first, vertical sorting patterns exhibit substantial structural state dependence over time. Second, structural state dependence is mostly present at the beginning of the market and retailers' responses to consumer demand become more important as the market matures.

The results presented in this paper suggest that, in the presence of downstream buyer power, producers opt for long-term contracts to ensure a distribution channel until they do not have any more incentive to continue. Since there are almost twice as many producers as there are retailers, retailers can decide which producers to buy from. Thus, producers must offer deals that are favorable to the buyer. Producers face a trade-off between maintaining a long-term trading arrangement with a retailer that will buy from them in the future and searching for other retailers that may buy at higher rates. In the presence of few downstream buyers, producers opt for ensuring a distribution channel by selling to the same retailer.

When the retailer landscape changes, it is not immediately clear a priori how the existing arrangements will change. On the one hand, they now have new retailers to sell their product to, so they do not have to rely as much on previous trading partners. On the other hand, there may not be as big of an incentive to switch if there are already efficiency gains from contracting with the previous trading partner. In this setting, the stability that producers gain from knowing a retailer will buy their product in such a competitive upstream market might cause them to stay put. In addition, large producers may be more able to satisfy product demand from new retailers than small producers. Small producers may be more likely to maintain the existing long-term contracts. Since theory alone does not authoritatively answer these questions, I take an empirical approach.

When more retailers enter the downstream market, the retailers' buyer power decreases since now producers have more outlets to sell their product. Producers are no longer obligated to continue offering favorable deals to the old retailer to maintain the relationship since now they can sell their product to a new retailer for potentially higher profits. When it comes to market outcomes, there are two countervailing forces at work. First, retailers may pay more for inventory as their buyer power decreases and producers have more outlets for distribution, leading to higher prices for consumers. Second, retailers obtain less profit from a more competitive downstream environment due to more retailers. I thus expect the distribution of profits to shift from retailers to producers as more retailers enter the market. The effects on consumer welfare are not a priori clear.

In vertically separated markets, the incentives of upstream and downstream firms may not be perfectly aligned. Moreover, in this industry, there are more producers than retailers and producers vary by size, meaning some firms have more influence over others. To ensure a stable distribution channel, producers may have an incentive to become close with one retailer instead of searching each period for a buyer. In this industry, most producers trade 80 percent or more of their inventory to one or at most two retailers in any county. Instead of serving another retailer in a given county, conditional on already serving one retailer in that county, the producer prefers to serve a first retailer in a different county. For a non-negligible percentage of producers, this pattern exceeds 95 percent of their inventory in any given county so in all aspects but literal, these firms act as if they were vertically integrated. This kind of time-invariant arrangement may solve bargaining inefficiencies and may act as a coordinate substitute for vertical integration.

The questions raised in this paper are important because one of the mandates of the WLCB is to regulate the cannabis market. The Board faces a trade-off between allowing firms to freely enter the market and have potentially excessive cannabis consumption and ensuring firms can flourish enough to keep the black market at bay. Its market design rules were also influenced by the alcohol laws, which after Prohibition, aimed to avoid the domination of the market by a few large firms through tied houses. It is important to understand how cannabis producers and retailers interact if the states are going to enact policies that aim to achieve specific market outcomes such as maintaining a certain level of consumption while warding off the black market with reasonable prices. Looking at the vertical arrangements in this industry is particularly important since there has been substantial debate on how these markets should be designed: for example, Colorado allows full vertical integration whereas Washington does not allow integration down to the retailer level. More states are following the steps of the early-adopter states so understanding the role of vertical arrangements in Washington State can guide future policy. Ultimately, regulators care about how the firms' arrangements may impact market outcomes, so it is important to understand why firms exhibit the observed patterns and use this information to guide policy recommendations. At the same time, the insights obtained from finding causal state dependence in vertical relationships can guide policy in any setting where vertical relationships play an important role.

In the absence of formal contracts, vertical arrangements are maintained if the market structure provides an incentive to do so and if there are frictions that are difficult to undo. If the market structure changes, it is not obvious whether and to what extent the existing vertical arrangements will continue to exist. The novel aspect in this project is that I examine the nature of vertical arrangements by observing sorting patterns for the universe of firm-to-firm transactions in the industry: there is no evidence of formal contracts, yet firms appear to derive some gain from maintaining a long-term relationship. I investigate the reasons why firms choose to enter vertical arrangements, the robustness of vertical contracts, and how these decisions affect market outcomes.

3.2 Related Literature

While there is a wide-ranging theoretical literature on vertical relationships, there is relatively little empirical research on the effect of market structure on vertical arrangements, despite their importance and their ubiquitous nature. Two persistent problems in the literature are lack of access to widespread supply-chain data and the endogeneity of contract formation: this project can address both issues.

First, I have data on an entire industry's supply chain. The Traceability dataset offers one of the most comprehensive looks into an industry's supply chain in the empirical industrial organization literature: I observe all firms in the Washington State recreational cannabis market, all transactions (firm-to-firm and sales), and detailed information on these transactions. Hansen, Miller and Weber (2020) were the first to use the transfers dataset to measure the impact of a tax reform on vertical structures. The Traceability dataset allows me to take a comprehensive look into vertical relationships in a way that was previously not possible.

Second, to tackle the endogeneity problem, researchers have generally followed two main approaches. First, researchers in the past have exploited the timing of the adoption of contracts as a source of exogeneity and looked at its impact on market outcomes. The second approach is generally to develop a structural model of the relevant economic forces, estimate it with existing contract data and relying on plausibly exogenous variation that can identify parameters, and conduct counterfactuals to investigate potential market outcomes. This paper studies issues often present in the first approach, which is that the act of entering into a contract is generally endogenous: if a firm enters into a contract, it must be because choosing to contract yields a higher expected payoff than not contracting. My main contribution is to exploit a novel dataset and a market reform that provided exogenous variation in trading patterns to uncover how changes in market structure affected existing vertical relations, namely how firms form or change their vertical relationships over time.

This paper is related to several strands in the vertical relationships literature, namely the vast theoretical literature and the relatively thinner empirical literatures on incentive alignments, exclusive arrangements, and bundling.

3.2.1 IO Theory

Different stories may motivate why firms enter into contracts. Matouschek and Ramezzana (2007) show how, depending on market conditions, agents may adopt exclusive contracts to reduce bargaining inefficiencies in the presence of private information. Transaction-cost arguments for vertical integration by Williamson (1998) come to mind, in which he points out that firms have incentives to vertically integrate if they foresee future disputes with other parties. In my setting, the large number of upstream firms may motivate producers to choose one retailer to exclusively trade with rather than to compete with the other producers in search of an outlet for their product. While these theoretical results may explain why the observed sorting patterns in the data are so stark, the results seem to suggest that the driving motives are producers' desire to secure a distribution channel and retailers' buyer power.

Williamson (1998) states that one of the critical dimensions to analyze transactions is uncertainty. Producers have an incentive to eliminate this uncertainty by either securing long-term relationships with retailers, or if they could, vertically integrate with a retailer or sell directly to consumers. So, if there is one thing that in this market firms would want to bring under internal organization, it is the demand uncertainty that producers face. Since the regulator does not allow vertical integration, a feasible alternative is to either form long-term contracts or develop a brand that consumers are familiar with in specific stores. This project measures the ways in which firms respond to the uncertainty in the market and how these responses change as the market matures and the uncertainty decreases.

3.2.2 Contracts and Incentive Alignments

Work on contract duration like Mackay (2017) comes conceptually close to my project, in which he analyzes the transaction costs of re-selecting a supplier and the cost of being matched to an inefficient supplier when the relationship lasts too long. Mackay's paper is akin to my project in the sense that information on buyer-supplier contracts are rare to obtain and his paper examines the incentives behind contract formation. One difference is that in his case, the buyer is fixed, the federal government, whereas in my market the downstream is oligopolistic and is subject to state regulations that alter its structure. This distinction will lead to differences in how firms behave. While I do not plan to go down the transaction costs route, I do consider the trade-offs that a supplier faces in the face of uncertainty when securing a buyer.

Mortimer (2008) studies the empirical effects of revenue-sharing contracts on firms' profits and consumer welfare in the video rental industry. She takes a structural approach after showing preliminary regressions of revenue-sharing contracts on retailer profits and shows how revenue-sharing contracts increase both upstream and downstream profits. In that industry, contracts between distributors and retailers arise out of the ability to monitor compliance through technological innovation. While my project also looks at vertical arrangements aligning firms' incentives, the reasons for why these arrangements arise and their effects are very different. One of the main empirical issues in the vertical arrangements literature is that contracts are endogenous by design, so it is difficult to isolate effects without a source of exogenous variation. I take a reduced-form approach to investigate what drives firms to engage in long-term contracts and to what extent, as market structure changes, firms find it useful to remain in these long-term arrangements.

3.2.3 Vertical Integration

Atalay, Hortaçsu and Syverson (2014) investigate firms' ownership of production chains to understand the effects of vertical integration. They use Census data, which features broad-based commodity flows across firms in various industries, and find that rather than facilitating transfers of goods, integration promotes efficient transfers of intangible inputs. While they focus on the role of integration within firms, I focus on the role of arrangements in a market where finding a buyer requires competing with many other firms. My setting does not allow integration but the observed arrangements, as a way for producers to secure a buyer, may have similar downstream effects as vertical integration.

Crawford et al. (2018) develop a structural framework for the analysis of vertical integration and use it to examine the welfare effects of vertical integration in the cable industry. There are two main distinctions from this paper. First, integration is not allowed in my setting: this leads to different incentives to develop sorting patterns. Second, a market reform provides exogenous variation on firms' sorting patterns, allowing me to impose less structure.

3.2.4 Exclusive Dealings

Asker (2016) evaluates the effect of exclusive dealing arrangements on competition in the Chicago beer market. While the arrangements I observe are the opposite of those in Asker and foreclosure is not a large concern in my setting, the observed sorting patterns may suggest a softening of upstream competition. While I also examine the effects of vertical arrangements on market outcomes, he looks at the arrangements in equilibrium, whereas I check whether they are robust to a change in the market structure.

Asker and Ljungqvist (2010) use bank mergers as plausibly exogenous variation to find that the apparent disinclination for firms to share underwriters has an impact on investment. In their setting, firms avoid sharing underwriters due to a demand for secrecy, so it is expected that the sorting patterns will remain unchanged. In my setting, however, the strategic incentives to maintain the same trading partner may disappear after the retailer license expansion. The main difference from their paper is that they assume the bank mergers are exogenous, whereas my variation stems from retailer entry after a reform unexpectedly expanded the number of possible licenses and from unexpected timing in actual entry from already licensed firms.

3.2.5 Firm Dynamics in a New Market

Another literature I contribute has to do with firm dynamics and how firms behave in a new market. Drawing inspiration from Doraszelski, Lewis and Pakes (2018) which measures learning in the new deregulated frequency response electricity market in the UK and from Huang, Ellickson and Lovett (2021) which measures how retailers learn to price liquor in the WA liquor market, I plan to measure consumer demand response at the retailer level of consumer demand and producers' quality in the new WA recreational cannabis market. Escudero (2018), similarly as in Huang, Ellickson and Lovett (2021), shows that prices in the WA cannabis market converge to a 50% markup, so firms are not setting prices as best responses to their competitive environment. I measure which firms retailers choose to trade with and the performance of new firms that act as producers based on what consumers demand. It is important to know whether markets get stuck in vertical relationships composed of firms with low performance due to high inertia, or whether markets reach a state with vertical relationships composed of firms with high performance due to retailers being in tune with consumers.

There is a wide literature about learning about prices and how prices converge to an equilibrium point, but not as much about other economic agents' quality or about optimal trading partners. The closest analog to this project is Osborne (2010), which measures learning and inertia at the consumer level for new products. Huang, Ellickson and Lovett (2021) document how retailers learn how to price liquor products upon deregulation and entry of new, private retailers. Escudero (2018), however, finds no learning of price-setting in my market and instead finds convergence toward rule-of-thumb pricing. Even if in this setting retailers are not pricing 'optimally', they might be listening to consumer demand and deciding which producer to trade with based on sales performance. To my knowledge, this is the first project to empirically test consumer demand responses and inertia at the supply chain level in a new market.

3.2.6 Vertical Relationships and Networks

The next literature to which this project contributes is the vertical relationships and networks literature. In a new market with new retailers, new producers, and new products, there is plenty of incomplete information and retailers and producers form links without having full information. Since we observe all vertical sorting patterns, we can learn a great deal about how an industry's vertical sorting patterns materialize and change over time. The asymmetry between retailers and producers in this market creates some interesting patterns: since there are more producers than retailers and some producers are much bigger in output/canopy size than others, this creates a prevailing uncertainty on whether producers can secure shelf space from retailers to sell their product. This leads producers to mostly sell to very few retailers, which resembles a semi-exclusive dealing situation. This is done to accomplish demand assurance for producers. Retailers have substantial bargaining power over producers and have market power at the retail level. The novel component here is examine the trading patterns between retailers and producers in a setting where vertical integration is not allowed, and what these firms do in the absence of VI.

3.2.7 Boundary of the Firm

Lastly, I contribute to the body of work regarding the boundary of the firm. This literature generally concerns itself with questions such as what do firms do when they cannot bring actions into their internal organization, and is it an efficient allocation of resources? What aspect of vertical relationships would then be brought under internal organization? Coase (1937) makes the distinction between market versus internal organization, but the regulator here only allows the use of the market. It gives us a unique glimpse at what the 'market' can achieve without internal organizations. Gibbons (2005) formalizes what it means to be a firm in four different ways, some of which are alluded to in this paper. Other papers that empirically test the boundary of the firm are Baker and Hubbard (2003) and

Garicano and Hubbard (2003).

3.3 Institutional Background

3.3.1 Retailer License Reform

The reform I exploit for my analysis was announced as a precautionary measure to ensure the recreational and medical markets could successfully merge starting July 2016. The merging of the markets meant that the medical dispensaries would need to acquire a recreational retailer license, and to sell medical cannabis, firms had to apply for a medical marijuana endorsement (MMJ). In practice, virtually all firms, medical or recreational, that applied for an MMJ received one. Prior to the merge, the medical market was mostly unregulated: there were no license quotas on retailers, retailers could grow their own product, and there was no product tracking. To properly merge the two sectors, the WLCB followed the advice of a consulting company and unexpectedly announced on December 15th, 2015 that, starting January 6th, 2016, it would increase the number of statewide licenses from 339 to 556. Table 1 shows how the number of available licenses changed across markets. The recreational license expansion varied by jurisdiction and it was determined based on the number of medical sales in each county. The top 10 counties received a 100 percent increase in the number of allowed licenses and the remaining counties received a 75 percent increase.

Four counties had a ban or moratorium on medical dispensaries, so they did not receive a recreational retailer license expansion. This detail is key for the treatment-control analysis: counties that did not receive a recreational retailer license expansion were not given one for reasons unrelated to their performance in the recreational market. This allows me to assign the counties/jurisdictions with a ban and moratoria as control groups without concerns that the decision to not grant them an expansion was due to a lack of performance. It is not immediately easy for consumers to substitute between medical and recreational products as they need to obtain a license from a physician. The literature on cannabis treats

Table 3.1: Change in Number of Retailer Licenses Across Markets

	Average	Q_{10}	Q_{25}	Q_{50}	Q_{75}	Q_{90}	Max
A. Firms (county markets)							
# (overall, before)	8.6	1	2	5	10	18	61
# (overall, after)	14.3	2	3	7	14	33	114
B. Firms (jurisdiction markets)							
# (overall, before)	2.2	1	1	2	3	6	21
# (overall, after)	4.5	1	2	3	5	9.6	42

(a) This table shows the distribution for the number of allowed licenses before and after the retailer license reform in the state of Washington. Panel A shows the number of retailer licenses when markets are counties and Panel B shows the number of retailer licenses when markets are jurisdictions. For reference, in all rows, the market with the most licenses includes the city of Seattle.

these sectors as separate markets. Beyond the counties that had a ban or moratoria, several jurisdictions within treatment counties had a ban or moratoria so these jurisdictions were not given an expansion either. I can in principle run our analysis on two different levels: treatment-control counties and treatment-control jurisdictions. For the sake of showing the main results, however, I show the results for counties only.

A key observation is that the license expansion did not immediately lead to entry. The WLCB would unexpectedly open the application window and it was easy for interested firms to send an application. The firms' reasoning for applying was that if there was the slightest interest in entering the market, it was better to apply while the application window was open than to wait until the next time it opened. During the last opening, October 2015, there were no rumors that there was going to be a license expansion. This last application window closed in March, two months after the measure went into effect.

Getting an application approved is not immediate and the first firms that entered the market after the reform were those that were approved before the reform was announced. To account for this timing feature, I will denote as entry due to the reform as any retailer that entered the market after March 2016 to allow some time to pass between the measure going into effect and firms entering the market. I will treat any firm that entered the market before March 2016 as a firm that had an application approved before the reform and was going to enter the market regardless.

One aspect that makes analysis of entry less clean than ideal is that in a substantial number of markets, the number of allowed licenses was greater than the number of retailers, which means that the quota was not binding. Figure 2 shows the actual number of active retailers as time progressed. Note that the total number of active retailers is less than the total number of available licenses. This translates into natural entry in these unsaturated markets. However, entry of this kind was occurring both in the treatment and in the control counties, so the first difference of the difference-in-differences research design should net the effect of these entries out.

3.4 Data

My main sources of data include cannabis retail sales, inventory transfers between firms, and laboratory sample potency results from the Washington Liquor and Cannabis Board.

The main dataset used in this paper is the universe of firm-to-firm inventory transfers from the WLCB Traceability System for the January 2015-December 2016 period, a total of 24 months. There is also a scanner dataset of all the final transactions to consumers. Merging the transfers with the inventory and scanner datasets yields a virtually complete description of the supply chain in this industry in Washington state. The dispensing data is used to construct the variables that measure the amounts of inventory sold each month.

The strengths of the dataset are clear, making it ideal to analyze vertical relationships.

Figure 3.1: Number of Active Retailers in Washington State Over Time

(a) The first line is the date when the reform was announced. The third line is after December 2016, end of the analytical sample.

One weakness of the dataset is the apparent inability to connect unintegrated producers' product with retailer sales since these unintegrated producers mostly send their product to independent processors, who in turn send the processed inventory to retailers. The extra layer of transfers complicates tracking. The silver lining is that only about 15 percent of producers are unintegrated with processors and most integrated producers process their own product [1]. I thus focus on integrated producers to avoid the inability to perfectly track the transfers. I combine the scanner data with inventory transfers to create a log of the inventory that flows through each retailer in a given month. I construct variables that track the stock of all products and how the stocks evolve over time as product is sold.

Yakima County serves as a representative example of the apparently exclusive pattern of inventory transfers between producers and retailers. Figure 2 shows the largest producers operating in Yakima County on the rows of the tabulation and the retailers, on the columns, that buy their products. Two retailers are omitted from the table since they were originally medical retailers and only entered the recreational market at the end of the 24-month period.

The first striking observation from Figure 2 is the large number of producers from all over the state that operate in a large county with only six retailers. The second observation is that when producers choose to trade in a county, they tend to trade the majority or virtually all their inventory with one or two retailers. The pattern becomes less drastic as the number of retailers in a county increases, as producers have more options to find a buyer. While the patterns make sense from the standpoint of a retailer, which would want to obtain products from varied firms, it is worthwhile to find out the motives for producers to engage with mostly one or two retailers in a given county.

It is important to emphasize the difference in one-off trades versus long-term trades when classifying by firm-pair/item versus classifying by firm-pair. In Figure 3 (a), when

[1] Conversations with industry participants appear to confirm the seemingly non-strategic role of processors.

Figure 3.2: All inventory transfers across time between producers, on rows, and retailers, on columns, for Yakima County

Tradename	HAPPY T..	STATION..	THE SLO..	WASHING..	Total
GROW OP FARMS ..	116	1,565	0	0	1,681
GOLDEN LEAF ..	0	0	1,393	0	1,393
ORGROW ..	37	0	1,272	0	1,309
GOLDEN TREE ..	0	0	782	0	782
GREEN FREEDOM ..	11	500	0	155	666
DOUBLE DELICIOUS ..	0	662	0	0	662
BUDDY BOY FARMS ..	0	470	0	0	470
HONU ENTERPRISES ..	0	397	0	45	442
ARTIZEN CANNABIS CO..	0	434	0	0	434
LIFE GARDENS 1 ..	26	14	299	0	339
MJ PRODUCTIONS ..	0	336	0	0	336
LEAPH ..	0	282	0	0	282
THE CALYX COMPANY ..	0	0	270	0	270
REDTAIL ..	27	91	149	0	267
F.O.L GENETICS ..	0	260	0	0	260
BMF WASHINGTON ..	26	74	93	33	226
COWLITZ COUNTY CANN..	0	0	219	0	219
BLUE SKY GROWERS ..	0	122	83	0	205
WA GROWER ..	0	202	0	0	202
SPINNING HEADS ..	0	10	184	0	194
STICKY BUDZ ..	83	4	29	54	170
GREEN LABS ..	0	11	122	29	162
M AND R DISTRIBUTIN..	0	38	0	119	157
FORBIDDEN GARDEN ..	0	155	0	0	155
NATURAL MYSTIC FARM..	0	94	0	58	152
MONKEY GRASS FARMS ..	0	0	148	0	148
FAIRWINDS MANUFACTU..	0	0	0	141	141
PIONEER FARM ..	0	139	0	0	139
TRICHOMETECHNOLOGIE..	0	137	2	0	139
DAWN STAR ..	0	135	0	0	135
GREEN REVOLUTION ..	0	73	36	18	127

only sorting by firm-pair, 28 percent of trades correspond to firm pairs trading once in the 24-month period. While this percentage is still high, most producers engage in some sort of long-term trading. The caveat, however, is that most of these long-term trades among firm pairs is composed of myriad different items, in which their prices are individually negotiated and agreed upon.

The first chart shows the tabulations of trades among firm pairs according to the number of months in which trading occurs. The second chart shows the tabulations of trades among firm pairs further classified by item description, according to the number of months in which trading occurs. In Figure 3 (b), one-off trading, which means a producer sells a retailer an inventory item once in a 24-month period, accounts for 55 percent of trades. I conclude that while the bulk of trading is composed of various items being traded once rather than one popular item being traded every period, most firms engage in some type of long-term trading.

The following three figures show the evolution of product offerings to retailers. Figure 4 shows how the number of products in the usable category offered by producers. The first few months do not differentiate between different usable types and in month 7, we see an average of about 15 usable products per producer. This statistic increases to about 30 by month 34. Figure 5 shows the evolution of product variety when we include the maximum number of products offered by producers: we can observe that the producers that offer the most products increase the number of product offerings over time. This pattern is consistent with new sizes, new product formats, and novel methods to process usable cannabis. Figure 6 shows the product concentration based on all their product offerings. Market concentration, when measured by producer, is very low and suggests an unconcentrated market at the

Figure 3.3: Tabulations of Trade Lengths for Washington State

nvals	Freq.	Percent	Cum.
1	298,706	55.08	55.08
2	102,620	18.92	74.01
3	49,577	9.14	83.15
4	29,345	5.41	88.56
5	17,702	3.26	91.83
6	11,716	2.16	93.99
7	8,294	1.53	95.52
8	5,582	1.03	96.54
9	4,153	0.77	97.31
10	3,071	0.57	97.88
11	2,367	0.44	98.31
12	1,795	0.33	98.64
13	1,473	0.27	98.92
14	1,179	0.22	99.13
15	931	0.17	99.31
16	912	0.17	99.47
17	836	0.15	99.63
18	598	0.11	99.74
19	464	0.09	99.82
20	461	0.09	99.91
23	202	0.04	99.95
22	132	0.02	99.97
21	118	0.02	99.99
24	44	0.01	100.00
Total	542,278	100.00	

(a) Trade duration by firm-pair/item

nvals	Freq.	Percent	Cum.
1	4,799	28.47	28.47
2	2,574	15.27	43.74
3	1,729	10.26	54.00
4	1,308	7.76	61.76
5	1,120	6.64	68.40
6	847	5.02	73.43
7	684	4.06	77.49
8	612	3.63	81.12
9	508	3.01	84.13
10	418	2.48	86.61
11	325	1.93	88.54
12	235	1.39	89.93
13	230	1.36	91.30
14	201	1.19	92.49
15	194	1.15	93.64
16	172	1.02	94.66
17	168	1.00	95.66
18	153	0.91	96.57
20	113	0.67	97.24
23	102	0.61	97.84
21	100	0.59	98.43
19	97	0.58	99.01
22	91	0.54	99.55
24	76	0.45	100.00
Total	16,856	100.00	

(b) Trade duration by firm-pair

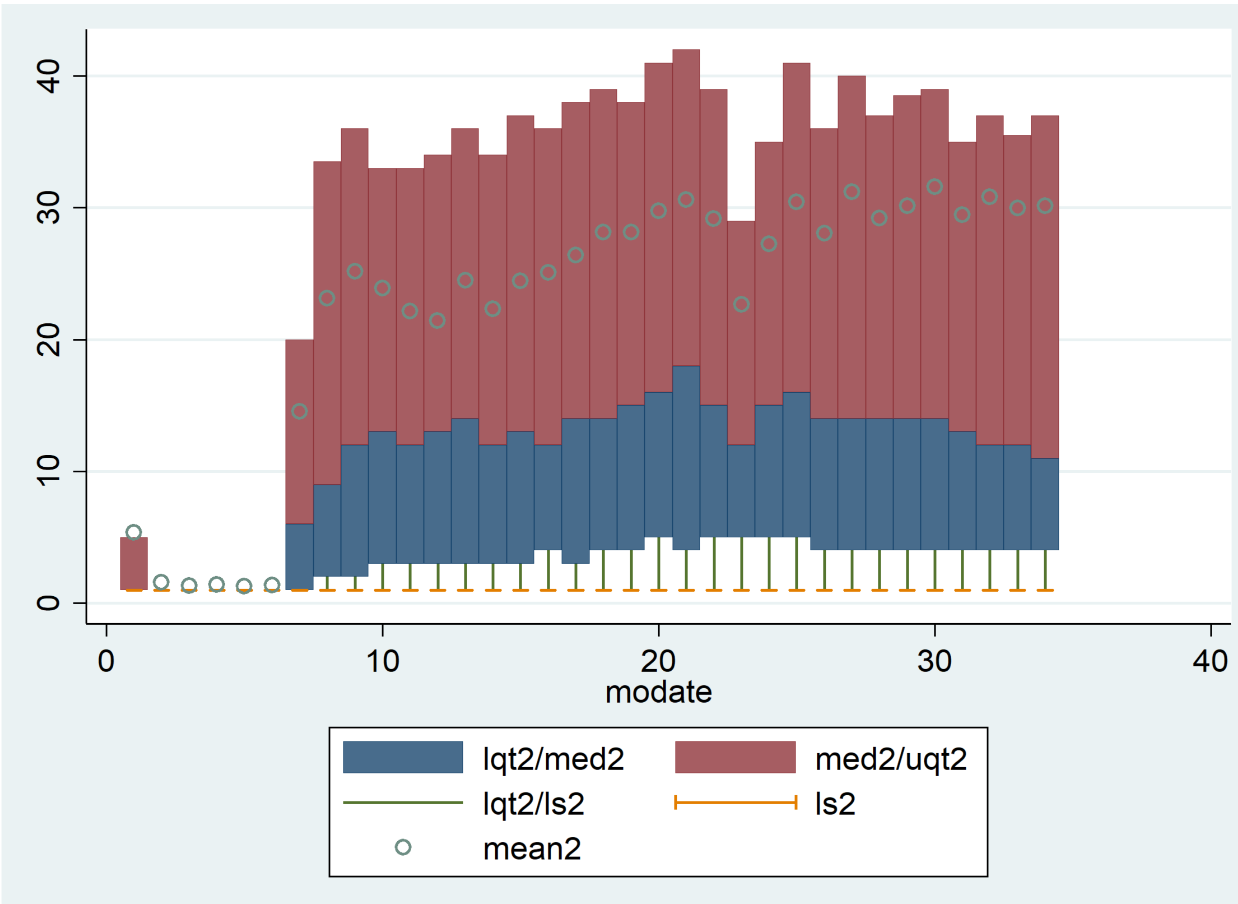
upstream level. The first six months look different in the figures because the regulator labeled all products as 'Usable'.

3.5 Model

Assume a model where we have the following agents: 1) Consumers in census tract h, 2) Retailers f, and 3) Producers i.

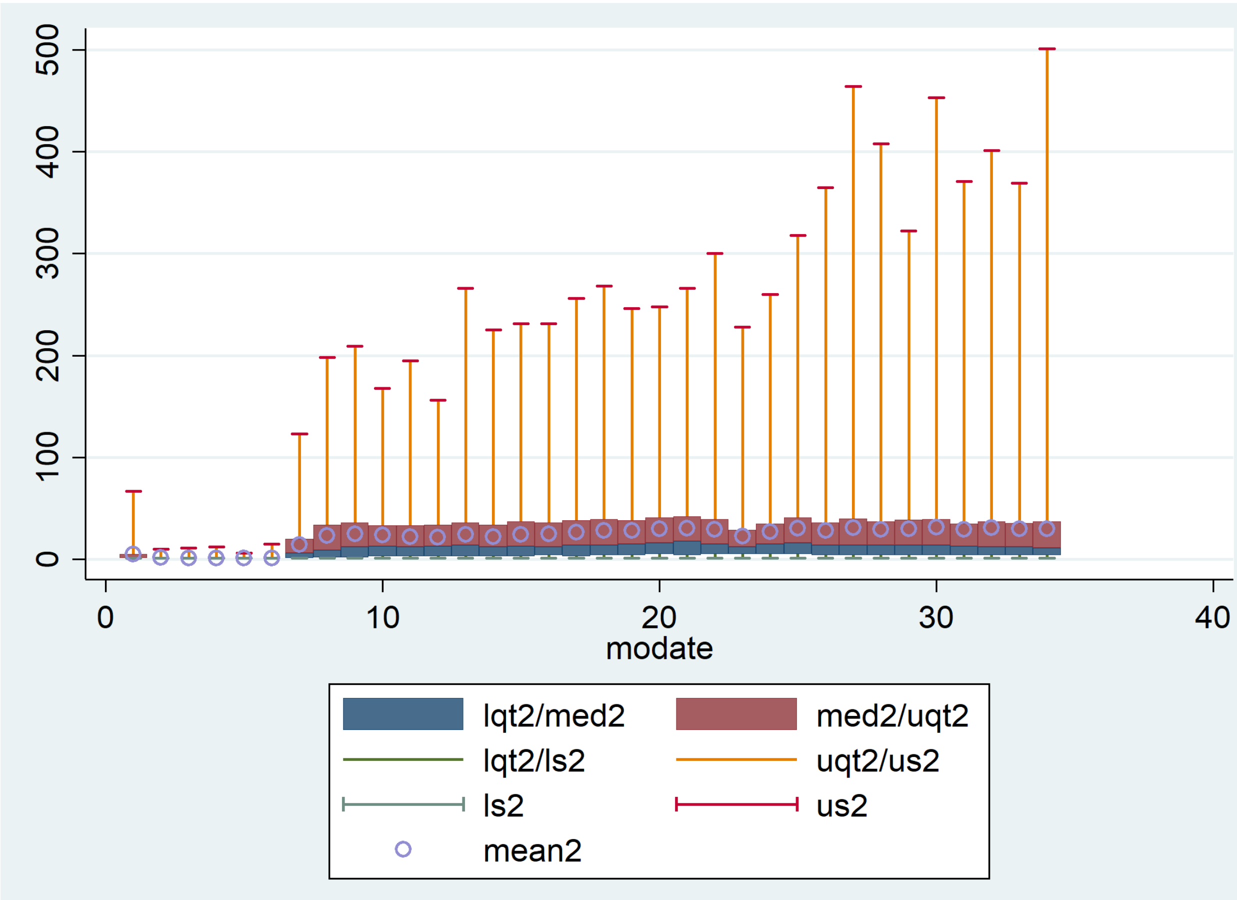
Producers are assumed to not be strategic agents: they exogenously provide goods each month. They know their own quality γ_i. Retailers are assumed to make strategic decisions on which producer to buy from and at what price: retailers' price-setting assumption is in line with the fact that retailer entry was heavily restricted, but producer entry was unrestricted, leading to a substantial degree of buyer power. Consumers visit a nearby store and purchase a product.

Figure 3.4: Evolution of products - Product Variety, maximum excluded



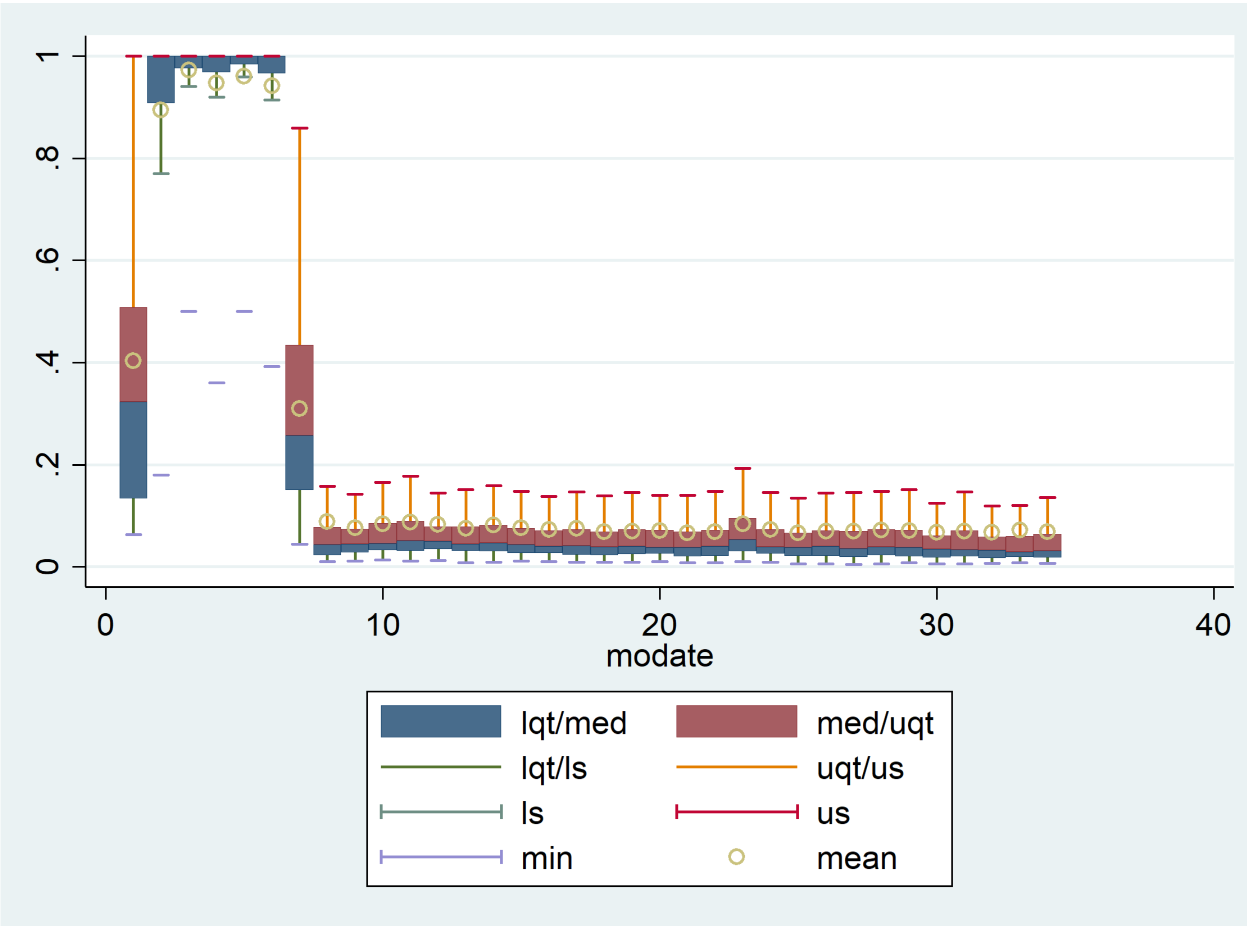
Months 1-6: inventory is under one 'product name', "Usable". There is some increase in the number of products offered over time until it stabilizes. The dots represent the monthly mean number of products. The lqt2/med2 measure represents the monthly range of products that lie between the lower interquartile range and the median and the med2/uqt2 measure represents the monthly range of products that lie between the median and the upperquartile range. The boundary between the two vertical bars is the median at a given month. This figure is provided for clarity.

Figure 3.5: Evolution of products - Product Variety, with maximum included.



Some outlier producers offer more and more products over time. The dots represent the monthly mean number of products. The lqt2/med2 measure represents the monthly range of products that lie between the lower interquartile range and the median and the med2/uqt2 measure represents the monthly range of products that lie between the median and the upperquartile range. The boundary between the two vertical bars is the median at a given month. This figure, provided for completeness, is less clear than Figure 4 since the maximum in a given month can be very right-skewed compared to the rest of the distribution for product variety.

Figure 3.6: Producers' products (weight) HHI over time.



Producers, overall, are diversified in their product offerings. The dots represent the monthly mean number of products. The lqt2/med2 measure represents the monthly range of HHIs that lie between the lower interquartile range and the median and the med2/uqt2 measure represents the monthly range of HHIs that lie between the median and the upperquartile range. The boundary between the two vertical bars is the median HHI at a given month. The min represents the minimum HHIs.

3.5.1 Timing

The timing is as follows: First, producers decide which products to offer and the quality of their products. Second, retailers decide which producers to buy from. Third, consumers decide which products to buy from the retailer.

At the end of each month, retailers 'gather' the signals about products based on consumer purchases and use this new information for next month's purchases.

A product j is defined at the producer level ij, but an observation is at the $ijft$ level. Products are aggregated up to the category level, out of 4 possible categories.

3.5.2 Consumer Demand

Consumers live in the geographic centroid of a census tract z. Based on a radius X miles away from the centroid, they have a number of retailers as options to purchase products. Their choice set is $\mathcal{B}_h = \{j \in \mathcal{J}_f | d_{hf} \leq r_h\}$, where r_h is the maximum distance for each census tract that guarantees consumers have at least 3 firms to choose from. I assume consumers know about producers' brand quality.

Consumers choose a product according to a discrete choice problem:

$$u_{zjift} = \alpha p_{jift} + X_{zjift}\beta + \xi_{ift} + \epsilon_{zjift} \tag{3.1}$$

where $\xi_{ift} = \xi_i + \xi_f + \Delta\xi_{ift}$.

By specifying the idiosyncratic error term as a TIEV, we can aggregate these utilities thanks to the logit's convenient form and obtain quantities.

$$Q_{jift} = \sum_z s_{zjift}(\xi_{ijft})M_z \tag{3.2}$$

where $s_{zjift} = s_{zjift|f} s_{zft}$ is the choice probability that a consumer in census tract z chooses product j by producer i at retailer i in month t.

3.5.3 Retailer decision

Retailers' profits are written as:

$$\pi_{ft} = \sum_{j \in \mathcal{J}_f} (p_{jft} - c_{jft}) Q_{jft} \tag{3.3}$$

Retailers, each month, maximize profits. They have two decisions: first, choose suppliers and second, set prices.

3.5.4 Price Setting

Given products and competitors, we could model this stage in two different ways. I assume firms play a Nash-Bertrand game, and we obtain the standard FOCs [2].

3.5.5 Link Formation/Producer Choice

Retailers, each period, choose whether to buy from a certain producer or not. Generally, a retailer would purchase from a producer again if the product sold well. Note, however, that it is difficult to break vertical relationships mainly due to the work that comes from setting up the relationship in the first place. This decision to restock from a producer depends on whether the stock has decreased by a certain amount in a given month. Thankfully, I observe these inventory flows between producers and suppliers each month.

Thus, the decision for restocking for a retailer can be modeled as a profit maximization problem where a retailer chooses an optimal bundles of products:

[2] A different way is to use a rule of thumb as in Escudero (2018) and set a markup of about 50%.

$$\mathcal{J}^*_{ft} = argmax_{\mathcal{J}} \ \pi_{ft}(X_{ijt}, c_{ijt}, \xi_{ijft}, \mathcal{H}_{t-1}) \tag{3.4}$$

where $\mathcal{J}^*_{ft}$ is the optimal bundle of products that retailer f chooses to purchase and $\mathcal{H}_{t-1}$ is the history of past purchases.

In summary, the inertia channel is manifested through retailers continuing purchasing from the same producers regardless of product performance. The 'consumer demand' channel is manifested through retailers responding to what consumers purchased.

3.6 Econometric Model

I do not attempt to directly estimate the model [3]. Instead, I search for evidence of the channels in the link formation stage. I estimate Equation (3.5) with the assembled dataset. The goal of this exercise is to measure the effect of history $\mathcal{H}_{t-1}$ on current inventory decisions versus the effect of consumers demand certain products. We can measure these effects through a linear probability model:

$$Trade_{jift} = X_{jift}\beta + \alpha Stock_{jf} + \beta Trade_{jif(t-1)} + \gamma InvSold_{jif(t-1)} + \epsilon_{jift} \tag{3.5}$$

Where $Trade_{jift}$ denotes whether retailer f buys product j from producer i in month t, X_{jift} are product characteristics such as potency, weight, product category, retailer and retailer zipcode fixed effect, $Stock_{jf}$ is a variable that measures a product j's performance at that retailer, $Trade_{jift'}$ denotes whether the two firms have traded in the near past [4], and $InvSold_{jif(t-1)}$ denotes the amount of inventory sold in the last month.

[3]This could be done in a future iteration of this paper, however, to empirically test competing theories of learning, understand equilibrium dynamics, or quantify how the process of branding happens.

[4]I use data going back up to 3 months.

Stock is defined as the cumulative quantity Q_T of product ji purchased by retailer f over time, minus the quantity sold to consumers Q_{ijft}. We can define Stock as $Stock = Q_T - Q_{ijft}$. The $InvSold$ variable should capture the role of consumer demand and the $Trade$ variable should capture inertia. A product that gets repurchased regardless of its performance is attributed to be due to the inertial pull between the existing vertical relationship.

3.6.1 Endogeneity Concerns

It may be difficult to estimate the role of inertia with a dynamic panel model since the errors may be serially correlated. The main idea behind the identification for this model is that the amount of product sold yesterday is not correlated of the product purchased from producers yesterday, as the product sold yesterday was already in stock for periods before $t-1$. In addition, we have retailer entry occurring each month, a product of the entry process. In the state dependence literature, we generally need some sort of exogenous variation that can disentangle structural state dependence from unobserved heterogeneity and this timing assumption appears to provide the required variation.

I argue that the $InvSold$ plays an important role in ameliorating the endogeneity problem that stems from serial autocorrelation. A retailer may purchase from a producer simply because they like the producer, and that channel may both appear in the lagged $Trade$ variable and in the error term. The amount of inventory sold last period helps account for the unobserved heterogeneity that may be included in the error term [5]

3.7 Results

I perform a variety of reduced-form analyses to understand the nature of nascent vertical relationships. I do so by exploring decisions to purchase from a supplier both at

[5] If endogeneity is not fully corrected after accounting for lagged inventory sold, one could implement an Arellano and Bond (1991)-style estimation procedure to make sure the errors are not serially autocorrelated.

the intensive and extensive margins. I run the analyses through the entire dataset and then look at several periods of the market's evolution over time [6]. I begin by examining how the extensive margin. Table (3.6) shows the relationship on whether a retailer purchases from a producer while measuring the stock based on revenues. Whereas the impact of the inventory sales variable and the current inventory stock appear to have a null effect on whether retailer i purchases product from producer j, past purchases appear to have an impact on present purchases from that producer. Interpreting the coefficients from the linear probability model, we can conclude that over the entire sample period, purchasing from a producer yesterday leads to a 23% probability increase of purchasing product from that producer today, an economically significant amount. The early stages of the market exhibit greater state dependence and the later stages of the market exhibit little to no state dependence. The patterns also appear when I look at the role of consumer demand response and inertia at the extensive margin in table (3.7) when looking at quantities instead of revenues.

Table 3.2: Empirical Analysis of Vertical Relationships on the Extensive Margin- Revenues

$$Trade_{[i=j]t} = \beta Trade_{[i=j](t-1)} + \alpha Stock_{(t-1)} + \gamma InvSold_{(t-1)} + \delta X + \epsilon_{ijt} \tag{3.6}$$

	Full	t<14	t>14	10<t<30	t>27	t<27
β	0.23*	0.34*	0.082*	0.131*	−0.192*	0.12*
R^2	0.38	0.15	0.18	0.22	0.06	0.16
N	55,063	10,873	42,896	33,719	18,663	26,527

γ and α null in all specifications.
*= stat. sig. at 1%

Table (3.8) examines the effects of consumer demand response and inertia at the intensive margin. The structural state dependence patterns mimic those found with the

[6] In the results, coefficients not present in a table are economically and statistically insignificant, and are thus excluded from the tables for clarity.

Table 3.3: Empirical Analysis of Vertical Relationships on the Extensive Margin- Quantities

$$Trade_{[i=j]t} = \beta Trade_{[i=j](t-1)} + \alpha Stock_{(t-1)} + \gamma InvSold_{(t-1)} + \delta X + \epsilon_{ijt} \tag{3.7}$$

	Full	t<14	t>14	10<t<30	t>27	t<27
β	0.23*	0.34*	0.083*	0.13*	−0.19*	0.27*
R^2	0.39	0.15	0.27	0.22	0.19	0.43
N	55,063	10,873	42,896	33,719	18,663	34,098

γ and α null in all specifications.
*= stat. sig. at 1%

extensive margin specification, where I find evidence of substantial structural state dependence at the beginning and little to none toward the end of the sample period. I also find positive and economically significant estimates for the amount of inventory sold last period, meaning that retailers respond to consumers purchasing products by buying again from that producer. These patterns appear mainly toward the end of the sample period. Caution is recommended for this specification since revenues include both quantities and price, and it is hard to infer whether these patterns are driven due to prices colliding with quantity-related sale patterns. To further explore this, table (3.9) examines the role of consumer demand response and inertia at the intensive margin for quantities alone. The patterns for structural state dependence and consumer demand response due to inventory sold become more apparent here. In these last two specifications, greater stock is associated with a negative likelihood of purchasing from that producer, which is expected due to limited inventory space.

As an additional check, I look at whether there is evidence of cross-effects: the impact of past trade at the extensive margin on today's intensive margin in revenues, shown in Table (3.10), and in quantities, shown in Table (3.11). The former only appears to show evidence of existence of consumer demand response at the intensive margin, especially in the later stages of the market. However, the specifications suggests economically and statistically insignificant effects for inertia effects and precisely estimated economically small negative

Table 3.4: Empirical Analysis of Vertical Relationships on the Intensive Margin- Revenues

$$InvPurch_{[i=j]t} = \beta InvPurch_{[i=j](t-1)} + \alpha Stock_{(t-1)} + \gamma InvSold_{(t-1)} + \delta X + \epsilon_{ijt} \tag{3.8}$$

	Full	t<14	t>14	10<t<30	t>27	t<27
β	0.15^{*}	0.14^{*}	0.15^{*}	-0.0003	-0.10^{*}	0.1^{*}
γ	0.073^{*}	0.002	0.03^{*}	0.111^{*}	0.06^{*}	0.073^{*}
α	-0.025^{*}	0.014^{*}	-0.06^{*}	-0.03^{*}	-0.2^{*}	-0.03^{*}
R^2	0.18	0.06	0.03	0.04	0.06	0.13
N	55,063	10,873	42,896	33,719	18,663	26,527

Table 3.5: Empirical Analysis of Vertical Relationships on the Intensive Margin- Quantities

$$InvPurch_{[i=j]t} = \beta InvPurch_{[i=j](t-1)} + \alpha Stock_{(t-1)} + \gamma InvSold_{(t-1)} + \delta X + \epsilon_{ijt} \tag{3.9}$$

	Full	t<14	t>14	10<t<30	t>27	t<27
β	0.17^{*}	0.48^{*}	0.02^{*}	-0.17^{*}	0.16^{*}	0.25^{*}
γ	0.25^{*}	-0.05	0.28^{*}	0.2^{*}	0.28^{*}	0.12^{*}
α	-0.01^{*}	-0.08^{*}	-0.06^{*}	-0.02^{*}	-0.16^{*}	-0.01
R^2	0.25	0.16	0.15	0.13	0.01	0.18
N	55,063	10,873	42,896	33,719	18,663	34,098

effects for stock amounts. The latter shows similar qualitative results, but with more noise for stock effects and more negative but noisy effects for inertia effects.

Table 3.6: Empirical Analysis of Vertical Relationships of Extensive Margin Variables on the Intensive Margin- Revenues

$$InvPurch_{[i=j]t} = \beta Trade_{[i=j](t-1)} + \alpha Stock_{(t-1)} + \gamma InvSold_{(t-1)} + \delta X + \epsilon_{ijt} \tag{3.10}$$

	Full	t<14	t>14	10<t<30	t>27	t<27
β	148.3	2307.2	-45	-424	-261.1	563.8
γ	0.14^*	0.05^*	0.1^*	0.111^*	0.01	0.11^*
α	-0.02^*	0.02^*	-0.06^*	-0.03^*	-0.2^*	-0.025^*
R^2	0.15	0.08	0.03	0.04	0.03	0.12
N	55,063	10,873	42,896	33,719	18,663	26,527

Table 3.7: Empirical Analysis of Vertical Relationships of Extensive Margin Variables on the Intensive Margin- Quantities

$$InvPurch_{[i=j]t} = \beta Trade_{[i=j](t-1)} + \alpha Stock_{(t-1)} + \gamma InvSold_{(t-1)} + \delta X + \epsilon_{ijt} \tag{3.11}$$

	Full	t<14	t>14	10<t<30	t>27	t<27
β	-82.5	-64.1	-37.1	-244.5	-181.2	-13.6
γ	0.42^*	0.44^*	0.30^*	0.37^*	0.11^*	0.37^*
α	-0.06	0	-0.05	-0.06^*	-0.2^*	-0.002
R^2	0.25	0.16	0.15	0.13	0.01	0.18
N	55,063	10,873	42,896	33,719	18,663	34,098

Conversely, I look at whether there is evidence of the opposite cross-effect: the impact of past inventory purchases (intensive margin) on today's extensive margin in revenues, shown in Equation (3.12), and in quantities, shown in Equation (3.13). All coefficients in these two specifications are noisy null results.

$$Trade_{[i=j]t} = \beta InvPurch_{[i=j](t-1)} + \alpha Stock_{(t-1)} + \gamma InvSold_{(t-1)} + \delta X + \epsilon_{ijt} \tag{3.12}$$

$$Trade_{[i=j]t} = \beta InvPurch_{[i=j](t-1)} + \alpha Stock_{(t-1)} + \gamma InvSold_{(t-1)} + \delta X + \epsilon_{ijt} \tag{3.13}$$

3.8 Discussion

The empirical results in the previous section suggest some interesting implications. The various specifications show evidence of structural state dependence, suggesting firms face some difficulty breaking a link with its supplier/buyer and allowing us to dive deeper into when and to what extent responses to consumer demand and inertia occur. I find that inertia is mostly present at the beginning of the market and that firms for the most part respond to consumer demand patterns over time and is mostly present towards the end of the data sample. This behavior is consistent with the idea of markets reaching an equilibrium and firms becoming more in tune to their customers while under the presence of frictions. The empirical analysis also sheds light into the nature of these link formation decisions at the intensive and extensive margin.

More questions arise from these results: if I can measure consumer learning instead of response to consumer demand, we could perform some comparative statics on consumer welfare, retailer profits, and tax revenue under perfect information versus under imperfect information. From the firm point of view, it may be fruitful to investigate why certain brands grow and why others do not in a market that begins from day one. Given learning, the data could be used to test competing theories of firm learning: does learning occur through consumers or through retailers? Can we learn about the nature of the frictions? Many avenues of potential research open up from this analysis, especially on questions about brand building, network formation, and firm behavior on the equilibrium path.

3.9 Conclusion

In this project I study the role of consumer demand and inertia between retailers and producers and the incentives behind contract formation in the nascent Washington State recreational cannabis industry. I use administrative data from the Washington cannabis regulator to assemble a novel and comprehensive dataset of vertical relationships along the industry's supply chain. The estimates indicate that there is substantial structural state dependence in vertical relationships along the industry's supply chain, especially at the beginning of the market, suggesting the existence of long-term contracts. This suggests that firms are reluctant to sever their existing business links due to poorly performing products and thus serves as a cautionary tale against making assumptions about firms when not in equilibrium. However, the inertia effects become muted and insignificant as the market matures. As the market reaches an equilibrium, product performance becomes the leading factor for producer-retailer matching, which is expected as retailers become more in tune about consumers' preferences. The toy model helps motivate the empirical analysis and to help rationalize the findings.

These investigations can guide fruitful future research, targeting questions of learning and how firms reach an equilibrium in the presence of imperfect information. Future immediate work involves estimating the structural version of the economic model to more explicitly capture the role of learning and inertia, as well as testing various types of learning. The findings that arise from this work can help guide modeling assumptions for markets that are not yet in equilibrium and that share similar market conditions as the one in this case study, as well as quantify how far off a researcher would be if one assumed full information from the beginning.

Appendices

Appendix A

Appendix 1

A.1 Additional Details and Variable Construction

A.1.1 Maximum Simulated Likelihood

I explain how to alternatively estimate location-specific monthly fixed costs through maximum simulated likelihood. Before specifying the likelihood, I must add additional behavioral assumptions to make the game internally consistent. The reason for this is that the game is complete information and demand across jurisdictions and location sets is interrelated, so I am unable to form a likelihood by assuming each licensed firm's decision is independent of the other firms. To bypass this issue and ensure the game stays internally consistent, I change the subgame perfect equilibrium to a quantal response equilibrium. In this new setting, all firms receive a logit shock in the location stage, but each firm believes other firms do not receive the shock: this effectively introduces some bounded rationality in the game, and allows me to form the likelihood while ensuring firms play a sequential game that contains an equilibrium.

For a candidate parameter γ, I can approximate the likelihood by simulating location choices in all location sets using S draws from the joint distribution of unobservable shocks $\epsilon_f(a)$. Then the likelihood for location set m is the simulated percentage of y_m with the observed order $\mathcal{O}$:

$$Pr(y_m|x_m;\gamma,\mathcal{O}) = \frac{1}{S}\sum_s \mu(\hat{y}_{sm}(\epsilon_{sm},\gamma,\mathcal{O}) = y_m) \tag{A.1}$$

This is the percentage of the S simulated location choices which equate to the location choice y_m observed in the data. The complete simulated log-likelihood takes the form:

$$ln\hat{L}(\gamma) = \sum_{m=1}^{|LS|} lnPr(y_m|x_m;\gamma) \tag{A.2}$$

The parameters γ are found via a nonlinear search.

A.1.2 List of Location Sets

Based on these kinds of boundaries, I tackle the biggest challenge to feasibly estimating the model: I divide the City of Seattle into 8 location sets of roughly 20 census tracts each:

1) Northeast (northern city limits, east of I-5, west of Lake Washington, and north of 75th street),

2) Northwest (northern city limits, west of I-5, east of Elliott Bay, and north of 85th street),

3)UW/Wallingford/Fremont (south of North 75th street, east of Highway 99, north of Lake Union, and west of Lake Washington),

4) Ballard/Queen Anne (south of North 85th street, west of Highway 99, north of Denny Way, and east of Elliott Bay),

5) Downtown/Capitol Hill/Central District (south of Lake Union and south of Denny Way, north of Yesler Way and north of I-90, bounded between the bays),

6) Docks (between Hwy 509 and I-5, and parts of West Seattle and Mt Baker).

A.1.3 Walk-through of finding the entry game equilibrium

I describe a walk-through of how to find the equilibrium of the application game:

1) Draw N_m potential firms in a jurisdiction m.

2) If a jurisdiction has more than one location set, assign each potential firm to a location set in a manner proportional to the location set populations [1].

3) Start with an initial n_m applicants. For each of these numbers of potential firms, compute expected profits conditional on getting a license, $E[r_f(\cdot) - s_f(\cdot)|\mathfrak{I}]$ by taking expectations over orderings that will occur in location game. Compute expected profits $E[\pi_f|\mathfrak{I}]$ as in equation (1.33).

4) If a jurisdiction has more than one location set: start with a candidate $n_{\mathcal{A}_{jm}}$ for each location set $\mathcal{A}_{jm}$. Compute step 3 for each element in vector $\{n_{\mathcal{A}_{jm}}\}_j$. The most populous jurisdictions move first, and within a jurisdiction, the most populous location sets move first. If a location set has non-negative expected profits, increase $n_{\mathcal{A}_{jm}}$ by 1. Repeat until each location set reaches $n_{\mathcal{A}_{jm}}$ such that $E[\pi_f(n_{\mathcal{A}_{jm}} + 1)|\mathfrak{I}] < 0$.

Step 4) addresses the third point in the previous section: interactions between $n_{\mathcal{A}_{jm}}$'s in location sets. I assume that firms in a location set know how many firms will apply in other location sets and use this information to evaluate whether the cap will bind, and in turn adjust their decision to apply.

A.1.4 Measuring Welfare

A.1.4.1 Consumer Welfare

In the baseline estimation and in the counterfactuals, I measure consumer welfare in a familiar fashion to most research that specifies a consumer demand system like Berry, Levinsohn and Pakes (1995). The differences in consumer welfare will be driven by 1) differences in prices among retailers and 2) consumer proximity to retailers.

The consumer surplus formula takes the familiar form: $CS = \frac{1}{\alpha}E[max\{U_{ij}\}]$

[1] More populated location sets are assigned more potential firms.

A.1.4.2 Resident Externalities

In this section I explain how I use the reduced-form hedonic regression estimates to calculate resident welfare in the baseline and in the counterfactuals. My property data has property values in full, so first I convert them to yearly payoffs to homebuyers. I do this by equating the value of a house, which can be interpreted as the net present value, to the sum of future expected yearly payoffs. We can express this as

$$V = \sum_{t=1}^{T} \frac{F_t}{(1+r)^t} \tag{A.3}$$

where r is the annual interest rate, F_t is the annual payoff, and V is the sum of a T-year discounted sum of flows. The goal in this exercise is to convert the stock into a flow. Once the property value is decomposed, I calculate the 10-year net present value of the property to more accurately compare with the 10-year length that retailers are expected to operate.

I make additional assumptions to back out the yearly payoff from the property value V, which is observed. First, I set $r = 0.09$, $T = 30$, and assume F_t increases by 6% annually. With these values, I can back out F_0 for each property.

For each property, I determine 1) whether it is close to a retailer and 2) whether its assigned school is close to a retailer. If so, I multiply the property's F_0 flow value by the corresponding reduced-form parameter estimate. Finally, I sum over all affected properties to obtain the resident welfare value.

Several caveats are in place for this resident welfare calculation. First, the externality impact is for the average homebuyer, meaning I am not able to break down the externality for heterogeneous groups of consumers with this approach. An implication of this is that I will likely measure the impact toward groups that view cannabis retailers as a disamenity, such as families with children or people with conservative values, and underweigh the impact for those homebuyers that may have a preference for 1) being near a cannabis retailer and 2) not caring that a retailer is close to their assigned school. Second, I shut off the sorting channel: this means that when a counterfactual leads to firms closer to schools, I shut down the potential effect of residents deciding to sell their homes, which can decrease the property values even further. Larsen (2020b) develops a model of homebuyer demand and supply that accounts for 1) heterogeneous homebuyers and 2) equilibrium sorting to more accurately measure the resident welfare from cannabis retailer location. Third, since the data only features property sales, the welfare calculations are for homebuyers, not all residents, meaning it excludes renters. Fourth, it assumes households expect the market to stay the same in the future when they calculate their expected yearly payoffs from the property. This assumption could be considered innocuous if we were standing in 2014, where the rules of the budding market seemed set in stone, but looks less innocuous now that several changes were enacted such as doubling the number of licenses and relaxing the buffers for some of the sensitive-use areas. One promising factor supporting this last assumption is that the buffers for schools stayed the same in the entire state.

A.1.4.3 Tax Revenues

Since each counterfactual can yield potentially different number of licenses, locations, and retail prices, the final prices that consumers face will be different. We can compute the tax revenue that the state collects from each scenario with the following formula:

$$Tax = \sum_m \sum_j \tau_m p_j Q_{jm}(p_j) \tag{A.4}$$

where τ_m is the combination of local and state sales taxes.

The other side of the coin would involve computing the property tax revenues collected. Assume that property taxes are paid once a year and that appraisal (property value updating) takes place before the tax must be paid. The average levy rate on assessed value of properties in King County is 0.0925 percent. Most properties' assessed value and market value tend to be equal. Due to the nature of the limitations on tax rates in the state, each county has an average effective property tax rate, so measuring how the property tax revenue changes by counterfactual scenario would involve 1)assessing which properties are affected by the negative externalities, measure how much value is lost, and measure the difference in property tax revenue between the current and new regimes, given by the equation below:

$$\Delta Tax = \sum_{m} \sum_{i \in m} \tau_m (V_{i,new} - V_{i,old}) \tag{A.5}$$

The same caveats from measuring resident externalities apply to the measurement of changes in property tax revenues.

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